Knowledge Diffusion Through Dual-Track Vocational Education and Training – A Firm Level Analysis

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Christian Rupietta
from Germany

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Prof. Dr. Uschi Backes-Gellner
Prof. Dr. Rainer Winkelmann

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Chapter 1 Introduction

Knowledge is a key factor for innovation and productivity and therefore of central interest to workers, firms, policy makers and researchers. Knowledge is embodied in individuals and depends on the education an individual has chosen. Therefore the economic outcomes of differences in individuals' education (e.g., different levels or types) have a long lasting history in economic research (e.g., Becker, 1964; Nelson & Phelps, 1966). By distinguishing between academic and vocational education, researchers link the properties of each educational type to outcomes such as innovation and productivity (Krueger & Kumar, 2004a). While academic education is considered as more general and theoretical, vocational education is considered to be more specific and practical.

Recent research on academic and vocational education shows that vocational education is thought to have positive productivity and innovation effects in firms that operate in a lowly dynamic environment and apply old and established technologies (Krueger & Kumar, 2004a, 2004b). Contrarily, academic education is associated with positive innovation and productivity effects in highly dynamic environments (Krueger & Kumar, 2004a, 2004b). Similarly, Aghion and Howitt (2006) recommend tertiary education as a growth fostering policy instrument and refer to workers with secondary education as unskilled. From the perspective of these models, countries that rely strongly on vocational and secondary education, such as Switzerland, should not be highly innovative. Switzerland, however, is a highly innovative country that achieves top positions in innovation rankings (Weissenberger-Eibl, Frietsch, Hollanders, Neuhäusler, Rammer, & Schubert, 2011). Vocational education in Switzerland has high training standards and a strong future orientation (Ryan, Wagner, Teuber, & Backes-Gellner, 2010). Thus, characteristics devoted to secondary education in the models described above appear to be not applicable in the Swiss case. In Switzerland, secondary vocational education mainly consists of dual-track vocational education and training (VET) (i.e., the combination of vocational schooling and workplace training). The term “dual-track VET” covers a wide range of 3-4-year programs, students start after lower secondary schooling. For each training program a curriculum exists that regulates training content in vocational schools and in the workplace. These curricula are binding for all training companies in Switzerland and undergo frequent updating. The aim of this dissertation is therefore to analyze the effect of dual-track VET on innovation and productivity at the firm level.

To have an effect on innovation and productivity the VET system must be capable to collect knowledge on new technologies and to diffuse it to all firms that train apprentices. Knowledge collection and knowledge diffusion in VET systems are two differently explored topics. While the processes of knowledge collection in VET systems in general and in the Swiss VET system in particular are well described (e.g., Backes-Gellner, 1996; Gonon & Maurer, 2012), less is known on a VET systems' capability to diffuse knowledge (see Dalitz, Toner, and Turpin (2011) for a case study on vocational education in Australia). A key component for the integration of new knowledge in VET is social partnership (the cooperation of employer and employee associations and the government) (Bundesversammlung der Schweizerischen Eidgenossenschaft, 2002; Busemeyer & Trampusch, 2012; Wolter & Ryan, 2011). Because the skill requirements in dual-track VET are market-driven, revisions of contents in training curricula are mainly initiated by employer associations, which integrate their current and future skill demand in the curricula (Wolter & Ryan, 2011). The employer associations define the future skill demand and integrate, in cooperation with the social partners, new skills that are valuable to all training companies in the curricula (Wolter & Ryan, 2011). Due to this frequent revision of training curricula, new knowledge enters the VET system. Through the application of training curricula during workplace training and vocational schooling, new knowledge enters those firms that participate in dual-track VET. Thus the application of training curricula can be regarded as knowledge diffusion mechanism.

Up to now little is known whether firms benefit from participating in dual-track VET by achieving a higher innovativeness. Researchers mainly analyze monetary benefits firms might gain from dual-track VET (e.g., Wolter, 2008). Moreover Wolter, Schweri, and Mühlemann (2006) argue that benefits from a firm's participation in dual-track VET could also be in the form of technological spillovers. The identification of knowledge diffusion mechanisms within the VET system and the empirical analysis of the effect of training participation on firms' innovativeness is the main purpose of chapter two of this dissertation.

Chapter two identifies knowledge diffusion mechanisms in the Swiss VET system. A comparison between the structure of academic and vocational education reveals that training curricula are institutions for knowledge diffusion. The training curricula contain general knowledge that is relevant and valuable to all firms that train apprentices in a given occupation. A high frequency of curriculum revisions results in a high rate of knowledge diffusion in an industry. This high rate of knowledge diffusion leads to a higher innovativeness of firms (Lucas, 2009; Staley, 2011), because firms can integrate update knowledge more frequently in their own innovation process. This chapter analyzes firms training participation empirically. By using data from the Swiss Economic Institute (KOF) innovation survey, this chapter tests for an effect of training participation on firms' innovativeness. The empirical approach considers the potential endogeneity in a firm's training decision and uses firm age and firm language as instruments for training participation. The results show a causal effect of a firm's training participation on innovations. This effect is highly robust and stable throughout several specifications. Further analysis that control for training intensity show a positive association of training participation and innovation. Chapter two concludes with a discussion on further diffusion mechanisms and policy implications.

Firms' innovativeness does not solely depend on the inflow of external knowledge but also the use of internal knowledge sources is crucial. An important knowledge source firms can access directly is its workforce (Galunic & Rodan, 1998; Subramaniam & Youndt, 2005). The inducement of a knowledge flow among workers is necessary to achieve knowledge recombinations (Kogut & Zander, 1992) and thus new knowledge. Firms can induce this knowledge flow by applying HRM practices that foster interactions among workers (e.g., teamwork and job rotation). As HR theory suggests the integration of knowledge stock and knowledge flow into a single system, such a framework would be especially suitable to analyze the combinations of knowledge from vocationally qualified workers with those from academically qualified workers. The role of vocationally qualified workers and the analysis of complementarities with other workers and HRM practices are subject to the third chapter of this dissertation.

Chapter three analyses knowledge form dual-track VET in combination with academic knowledge and HRM practices. Following a theoretical model by Wright, Dunfold, and Snell (2001), this chapter integrates firms' knowledge stock (Human capital pool) and knowledge flow (induced by firms' HRM system) into a single knowledge creation KC system. This KC system captures complementarities between and within the human capital pool and the HRM system as expected in configurational HR theory. Although the theoretical literature on systems or typologies of human capital and HR practices is large (Delery & Doty, 1996), such systems have not been invested empirically. The empirical literature on human capital and HRM mainly focuses on the analysis of moderating effects (Bornay-Barrachina, De la Rosa-

Navarro, López-Cabrales, & Valle-Cabrera, 2012; De Winne & Sels, 2010). This chapter analyzes a KC system by applying fuzzy set qualitative comparative analysis (fsQCA). This method is particularly suitable as it considers several features of configurational theory like equifinality and causal complexity (Fiss, 2007). The data used for the empirical analyses are the same as described in chapter two. The human capital pool covers workers with different educational backgrounds (university degrees, degrees for professional education and training (PET) and dual-track VET degrees). The HRM system is operationalized by the use of teamwork, job rotation and empowerment practices. Furthermore the model considers industry dynamism and firm size. The results of the fsQCA show that the configurations of the KC system highly depend on the environmental dynamism. The taxonomy derived from the fsQCA results contains a mechanistic and an organic type that are consistent with those proposed by Burns and Stalker (1961). Two additional types constitute hybrid cases and either rely on a vocational-skill mix or on organizational learning.

Interactions among workers might not only influence innovativeness of firms but instead the productivity of interacting workers. Interactions of workers with different knowledge can lead to spillover effects and learning. These spillover effects are beneficial because they improve workers' productivity. Research on spillover effects generally investigates educational spillover effects in two ways: Studies focus either on spillovers form the highest educational level or the average educational level (e.g., Ciccone & Peri, 2006; Moretti, 2004b). Because workers with VET degrees are highly qualified professionals, also workers with a high educational degree (e.g., an engineer) might learn from interacting with workers with VET degrees (Backes-Gellner, Rupietta, & Tuor, 2011). This potential for spillover effects from lower educational levels but different educational types (reverse spillovers) remains unconsidered in the literature. This dissertation investigates spillover effects from dual-track VET in its fourth chapter.

Chapter four analyzes educational spillover effects from dual-track VET. For the development of a theoretical framework it draws form the literature on informational spillovers (Jovanovic & Rob, 1989). By arguing that differences in education generate different ideas and an idea exchange results in informational spillovers, chapter four integrates differences in educational type in the spillover framework. This chapter additionally investigates the functional form of the spillover effect and hypothesizes a positive but declining effect of the number of workers with dual-track VET degrees on the productivity of workers with tertiary degrees. For the analysis a large employer-employee panel is aggregated to the firm level and aggregated

Mincerian earnings equation are estimated. The estimation procedure includes fixed effects and IV estimation to consider the potential endogenous employment of workers with dual-track VET degrees. The results show a highly robust and statistically significant effect of the number of workers with dual-track VET degrees on the productivity of workers with tertiary degrees. As expected this effect is positive but declining. The results imply that knowledge from dual-track VET enhances the productivity of workers with tertiary degrees.

Chapter five concludes by synthesizing the key elements of the preceding chapters. It furthermore gives an outlook on further research questions that occur from the findings of this dissertation.

Chapter 2 Dual-track VET and innovation: a theoretical and empirical analysis of the advantages of dual education for innovation in firms

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2.1 Introduction

Firms require knowledge to be innovative (Dosi, 1988; Fagerberg 2005). Thus workers' knowledge is a crucial factor for firms' innovativeness. Workers knowledge results from his or her education. As education can differ in several aspects (e.g., level and type), these aspects influence the knowledge workers have. While the level determines the sophistication of knowledge, the type (academic or vocational) determines whether the knowledge a workers possesses is more theoretical or practical. Firms gain from the education of their workers by selecting workers according to their knowledge demand.

Academic and vocational education have gained different attention in the literature on education and innovation. The relation between academic education and innovation has been investigated theoretically and empirically at the macro and meso level. Studies focusing on the macro level (e.g., Aghion, Boustan, Hoxby, & Vandenbussche, 2005; Aghion & Howitt, 2006; Vandenbussche, Aghion, & Meghir, 2004) argue that academic education fosters growth rates of countries. Similarly, for the firm level, models by Krueger and Kumar (2004a, 2004b) imply that firms benefit from an academically qualified workforce. But it is not only academic education that provides workers with knowledge that is relevant for innovation. Also a special form of vocational education, curriculum-based dual-track vocational education and training (VET), provides workers with knowledge. It thereby follows nation-wide recognized curricula and combines theoretical education in vocational schools with practical education in workplace training. Both parts of dual-track VET provide the apprentice with knowledge that is highly relevant for their occupation, but little is known on the influence of dual-track VET on the innovativeness of firms.

We argue that the innovative potential in dual-track VET stems from its frequently updated curricula (Gonon & Maurer, 2012). Highly innovative firms participate in the updating process of such curricula and provide knowledge that is relevant for innovation (Wettstein & Gonon, 2009). This updating of curricula affects both, vocational schooling and workplace training, and thereby facilitates the knowledge flow within the VET system. Firms offering dual-track VET benefit directly from this knowledge flow and can therefore be expected to be more innovative.

The innovation process in firms offering dual-track VET is similarly structured like those in universities with top-tier PhD programs. During their PhD studies, PhD students combine research and coursework. Due to a frequent revision of the curricula, the PhD courses contain the latest knowledge on the field. During their coursework, PhD students learn about this knowledge and apply it in their research projects. The knowledge integrated in the courses thus directly influences the innovativeness of the PhD students' research. Similarly, apprentices learn in vocational schools the latest developments in their field. The curricula in the vocational schools are frequently revised according to the needs of the firms. During their work in their host firm, apprentices have the possibility to apply this knowledge in the production process. Thus, they contribute directly to the innovativeness of their host firm.

We integrate firms' participation in dual-track VET in a knowledge production function framework (Pakes & Griliches, 1984). Due to the participation in dual-track VET, new knowledge enters the firm. Firms combine this new knowledge with other knowledge sources and thereby achieve more possibilities for knowledge combinations than firms not participating in VET. We argue that the additional knowledge combinations provide a competitive advantage in the innovation process for training firms compared to non-training firms. Thus, we expect that training firms have a higher innovativeness than non-training firms.

By augmenting the knowledge production function proposed by Pakes and Griliches (1984), we derive our estimation equation. We estimate the knowledge production function by using OLS and GMM, because firms' decision to participate in dual-track VET might be endogenous. To identify the causal effect of dual-track VET on firms' innovativeness we apply an instrumental variable approach. In Switzerland firms' decision to offer dual-track VET is strongly related to tradition. This training tradition differs by the three linguistic regions (French, German, and Italian) in Switzerland. Firms in German-speaking regions have a stronger training tradition than firms in French- or Italian-speaking regions. We therefore use language as an instrument for firms' participation in dual-track VET. Moreover, firms' participation in dual-track VET declined slightly over the past five decades. Thus older firms are more likely to have an established training tradition that contains dual-track VET. Therefore we use firm age as an additional instrument to capture training tradition.

For our empirical analyses we use the KOF (Swiss Economic Institute) Innovation Survey. This panel data set comprises two to three thousand observations per wave and is representative for the construction, manufacturing, and service sectors in Switzerland. It contains information on various innovation outcomes such as patent applications, process and product innovations, and general innovation, a joint measure that combines the two latter measures. To analyze the effect of dual-track VET on firms' innovativeness we require these gradual innovation measures, because training curricula contain knowledge that is not patentable. The availability of these innovation measures allows us to analyze which impact dual-track VET has on innovations with various degrees of novelty.

Our results show that dual-track VET is positively associated with all innovation measures. When we take the endogeneity of firms' training decision into account, we can show that dual-track VET has a positive and highly robust impact on general innovation. These results have several theoretical and practical implications. By showing that dual-track VET has a positive impact on firms' innovativeness, we provide a theoretical and empirical explanation that not only tertiary and academic qualifications positively influence innovation, but also do secondary vocational qualifications. Although the findings appear to contradict recent recommendations made by scholars and international organizations (e.g., Aghion, 2008), our results are consistent with innovation and knowledge diffusion theory. Lucas (2009) and Staley (2011) argue that a rapid diffusion of knowledge within a country results in higher frequency of innovations and thus higher growth. Due to the participation in dual-track VET a training firm benefits from the knowledge that is diffused within the VET system and can be more innovative than firms not participating in this system.

2.2 Institutional background and theory

Typically, studies that investigate the influence of education on innovation argue that firms benefit more from general (academic) than from specific (vocational) education. Krueger and Kumar (2004a) distinguish between general and vocational education. They argue that the employment of workers with general education allows firms to adopt new technologies. Contrarily, workers with vocational education are associated with firms that apply old and established technologies (Krueger & Kumar, 2004a).[1]

[1] Krueger and Kumar (2004a, 2004b) show that general (university) education is not only beneficial for firms that constantly adopt new technologies but also that countries experience higher growth rates by putting more emphasis on general education. This view is consistent with other models that analyze countries' growth. Aghion and Howitt (2006) distinguish between tertiary (university) and secondary/primary education and argue that countries achieve higher growth rates by concentrating on tertiary education. The models by Krueger & Kumar

However, vocational education systems differ between countries and some forms of vocational education might be beneficial for innovation. We investigate a specific form of vocational education that predominantly firms in German-speaking countries offer: Dual-track VET.[2] This specific form of vocational education combines vocational schooling with workplace training in 3-4-year programs[3]. Similar to academic education, dual-track VET bases on curricula. These curricula regulate both education in vocational schools and training at the workplace. Curricula are nation-wide accepted and ensure the transferability of skills between companies (Wolter & Ryan, 2011). Thus the curricula contain general skills that are valuable for all companies.

Curricula in academic and vocational education, respectively originate from different institutions. While in academic education universities decide on the contents of their programs, in dual-track VET employers' associations together with employee and governmental representatives (social partnership) decide on the contents of the curricula (Bundesversammlung der Schweizerischen Eidgenossenschaft, 2002; Wolter & Ryan, 2011). To ensure that the contents of the curricula meet actual skill demands, mainly the employer organization initiate revisions of curricula and integrate innovations in dual-track VET (Bauder & Osterwalder, 2008; Bundesversammlung der Schweizerischen Eidgenossenschaft, 2002; Der Schweizerische Bundesrat, 2003)[4]. Thereby, the social partners integrate best practices into the revision of curricula (Bauder & Osterwalder, 2008). The resulting curricula base on skill requirements multiple firms have and have a strong focus on competences that a qualified worker in a certain occupation must have (Der Schweizerische Bundesrat, 2003; Pedró, Burns, Ananiadou, & de Navacelle, 2009). Moreover, the training standards resulting from these curricula are very high (Bierhoff & Prais, 1997; Ryan et al., 2010).

Figure 2.1 shows the characteristics of academic and vocational education and their contribution to firms' knowledge. Different from universities, the knowledge contained in the

(2004a, 2004b) and Aghion and Howitt (2006) share that workers with vocational education do not contribute to innovation because their education either lacks generality or sophistication.

[2] Dual-track VET is predominately offered by firms in German-speaking countries. We use the Swiss form of dual-track VET for our model as Switzerland is a case that contradicts recent theories on education and innovation. In Switzerland more than two thirds of a cohort that graduated from compulsory schooling opts for dual-track VET. Contrary to theory the innovativeness of Swiss firms is one of the highest in the world (Weissenberger-Eibl, Frietsch, Hollanders, Neuhäusler, Rammer, & Schubert 2011).

[3] For the duration of the training program, apprentices have a fixed-term contract with a firm. During their training apprentices are fully integrated in the production process and perform productive tasks that are similar or identical to those of qualified workers.

[4] Future-orientation and thus innovation is a key component of the Swiss VET system Bundesversammlung der Schweizerischen Eidgenossenschaft (2002) For an overview of innovation-fostering institutions in the Swiss VET system see Pedró, Burns, Ananiadou, and de Navacelle (2009) and Rauner (2008).

curricula of dual-track VET comprises future-oriented knowledge from all firms that participate in the curriculum setting process (shown in a simplified way by the bold lines). By participating in VET and offering apprenticeships, firms can internalize the knowledge integrated in the curricula. Apprentices thus transfer the knowledge from the curricula to their firm.

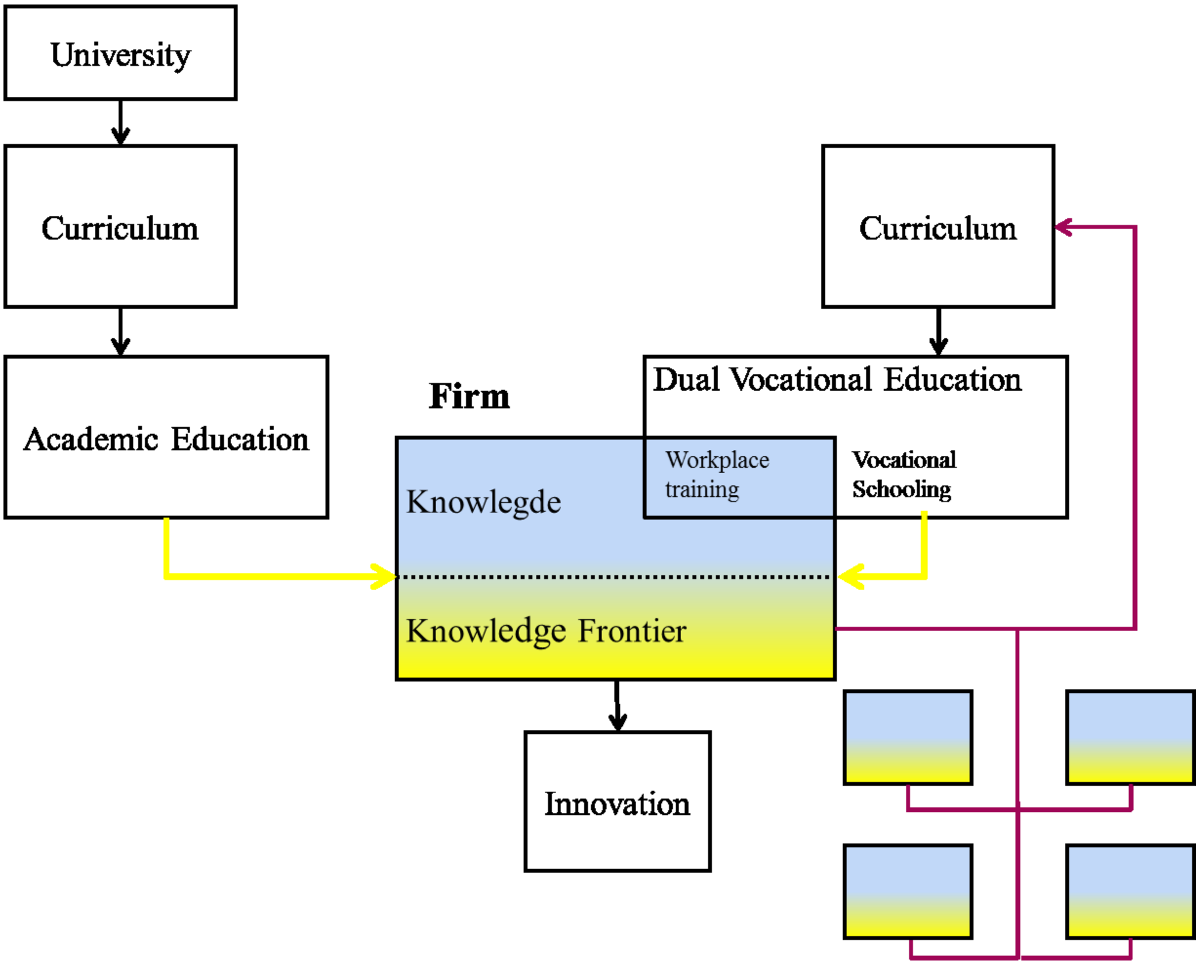

Figure 2.1 – Origins of academic and vocational knowledge and its integration in firms.

The knowledge transfer from the curricula and its influence on firms' innovation shares several similarities to the knowledge transfer in top-tier PhD education. Similar to the apprentices, PhD students combine formal schooling in a course program with workplace training (supervised research). By participating in several courses held and designed by experts in their fields, PhD students learn about the latest theory and methods that are relevant for their own research. Due to research collaborations between PhD student and supervisor, the supervisor gets access to the knowledge the PhD student learned during his or her course work. Thus the supervisor can update his or her knowledge and the knowledge of his research group through the collaboration with a PhD student who participates in top-tier PhD courses. As a result, the research projects of the entire group might be more innovative.

We translate this example to apprentices and their firms. By receiving training on latest technological developments in vocational schools, apprentices can transfer this knowledge to their firm. This knowledge can spread in the entire firm and enables it to introduce new technologies and to improve products and processes. Thus due to the participation in dual-track VET, training firms can improve their innovativeness.

The example shows that knowledge contained in curricula of dual-track VET diffuses among training firms. Due to frequently updated curricula, all firms that participate in training benefit from latest technological developments and immediately have labor that helps to implement these technologies. By linking dual-track VET to economic theory on knowledge diffusion we can derive implications of knowledge diffusion for firms' innovativeness. Recent studies on knowledge diffusion and innovation show that a higher rate of diffusion begets a higher rate of innovation (Lucas, 2009; Staley, 2011). For an individual firm a higher rate of knowledge diffusion results in a frequent update of information on new technologies (Staley, 2011). Firms that participate in dual-track VET thus receive updates on new technologies more frequently than firms that do not participate in such training. Consequently, we expect training firms to have a higher probability to innovate compared to non-training firms holding the rest constant. We therefore hypothesize:

H1: Firms that participate in dual-track VET become more innovative than firms that do not participate in dual-track VET.

For the empirical investigation of our hypothesis we need to investigate firms' knowledge production process. Therefore we augment a knowledge production function framework proposed by Pakes and Griliches (1984) by firms training participation. Before integrating firms' participation in dual-track VET as an additional factor that contributes to knowledge growth, we describe the data that underlies our empirical analysis.

2.3 Data

2.3.1 Sample and descriptive statistics

For our empirical analysis we use the Innovation Survey of the Swiss Economic Institute (KOF). The KOF collects the data triennially since 1990 and includes several innovation indicators such as process and product innovation, and patent applications in the questionnaire. These three innovation indicators are binary and take the value of one if a firm innovated or applied for a patent during a three-year period. We use the process and product innovation indicators to construct a fourth innovation measure. This binary measure takes the value of one if either product or process innovation takes the value of one and thus is an indicator for general innovation activity. Thus we title this constructed measure general innovation.

Table 2.1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent variables					
General innovation	2936	0.725	0.446	0	1
Product innovation	2936	0.633	0.482	0	1
Process innovation	2936	0.520	0.500	0	1
Patent applications	2936	0.192	0.394	0	1
Explanatory variables					
Training firm	2936	0.723	0.447	0	1
Firm size (Number of workers)	2936	174.507	515.450	1	8371
Share of workers with university degree	2936	0.059	0.118	0	1
Share of workers with degree higher than VET	2936	0.159	0.153	0	1
Share of workers with apprenticeship degree	2936	0.509	0.239	0	1
Share of workers with degree lower than VET	2936	0.273	0.249	0	1
Non-price-competition	2936	0.420	0.494	0	1
Price-competition	2936	0.720	0.449	0	1
Increase in estimated demand for next 3 years	2936	0.426	0.495	0	1
Foreign firm	2936	0.134	0.341	0	1
Lack of skilled workers	2936	0.166	0.372	0	1
Sector					
Manufacturing	2936	0.582	0.493	0	1
Construction	2936	0.066	0.248	0	1
Service	2936	0.351	0.478	0	1
Year					
year 1999	2936	0.197	0.397	0	1
year 2002	2936	0.286	0.452	0	1
year 2005	2936	0.300	0.458	0	1
year 2008	2936	0.218	0.413	0	1
Region					
Lake Geneva Region	2936	0.013	0.115	0	1
Espace Mittelland	2936	0.213	0.409	0	1
Northwestern Switzerland	2936	0.173	0.378	0	1
Zurich	2936	0.238	0.426	0	1
Estern Switzerland	2936	0.248	0.432	0	1
Central Switzerland	2936	0.115	0.320	0	1
Instruments					
Firm age	2936	59.966	42.295	1	351
German-Speaking firm	2936	0.985	0.120	0	1

The data set contains detailed information on the educational composition of a firm's workforce. We use this information to construct our main explanatory variable: firms' participation in dual-track VET. The KOF classifies workers into 5 categories: workers with university degrees, workers with degrees higher than VET, workers with VET degrees, workers with degrees lower than VET, and apprentices. We generate a binary variable entitled "training firm" that takes the value of one if a firm employs at least one apprentice and zero otherwise.

To investigate the influence of dual-track VET on firms' innovativeness, we exclude observations from waves 1990 to 1996. These waves do not provide the necessary information either for the innovation measures or for the main explanatory variables. We furthermore restrict our sample to German-speaking regions as dual-track VET is more widespread in these regions.

Table 2.1 contains descriptive statistics for our estimation sample. More than 50% of the firms in our sample report either a process innovation or a product innovation. Compared to the number of firms that applied for a patent (19.2%), these number show that we measure innovations with different significance and novelty. While process and product innovations might include innovations that are new to the firm, innovations that are patentable might be either new to the world or new to the industry.

Firms in our sample are on average larger than the average firm in Switzerland. The KOF survey applies a sampling scheme that oversamples large and medium-size firms. Moreover, as most of the firms that report missing values are small, our remaining sample represents large and medium-size firms stronger. The stronger representation of large and medium-size firms does not threaten the validity of our results as we focus on the effect of dual-track VET on firms' innovativeness in general not on the estimation of a representative effect for Switzerland.

2.3.2 Instrumental variables

The data set includes valuable information for the construction of instrumental variables for firms' training decision such as information on firms' age, the location of the firm, and the language spoken by the employees. Dual-track VET in Switzerland has a long-lasting tradition and gained its popularity in the mid of the 20th century (Knutti, 2007). Due to the adoption of dual-track VET and its integration in firms' organizational structure, we expect that older firms developed a training tradition that relies on dual-track VET. Although dual-track VET is still highly recognized and wide-spread in Switzerland, we expect younger companies not to have such a highly established training tradition compared to older companies. Therefore we choose firm age as an instrument for firms training participation.

As we cannot assess the validity of the instrument in the just-identified case, we choose an additional instrument to conduct robustness checks of our IV specification. The additional instrument we use is also related to firms training tradition. Firms' training traditions differ by the three linguistic regions (French, German and Italian) in Switzerland. Firms located in the German-speaking part of Switzerland typically are more likely to offer dual-track VET programs than firms located in the French- or Italian-speaking part (Gonon & Maurer, 2012; OPET, 2010). As the data set contains linguistic information at the postcode level and at the firm level, we combine both measures to construct an instrumental variable.

The KOF makes an initial assignment of the questionnaires to firms based on a linguistic categorization provided by the Swiss Post. If a firm is unable to fill in a questionnaire due to linguistic difficulties it has the possibility to request a different linguistic version of the questionnaire. Having this information, we can construct a binary variable that indicates whether firms' language is German or not. As our sample contains only firms that are located in German-speaking regions, we expect all firms that returned a German questionnaire to have a stronger training tradition than the remaining firms in our sample.

2.4 Estimation strategy

For our empirical analysis we augment the knowledge production function proposed by Pakes and Griliches (1984). Their original model contains two equations: The first equation explains knowledge growth by a firm-specific productivity shifter, a time trend and past period's research expenditures. The second equation explains the generation of patents with a time trend and knowledge growth. We augment this framework by introducing the knowledge that the training curricula of dual-track VET contain as an additional factor that enhances the knowledge growth of a firm. Following Pakes and Griliches (1984) we include firms' knowledge growth in the patent equation and allow for the occurrence of other innovation outcomes that summarize non-patentable knowledge. Thus product and process innovation are considered as outcomes of firms' knowledge growth.

We adapt this equation to our available variables. We operationalize firms' application of training curricula by its participation in dual-track VET.[5] We estimate a linear probability model, because we have binary innovation measures taking the value of one if the firm innovated successfully during the observation period and zero otherwise. The advantage of the use of the linear probability over probit models is the direct calculation of the marginal effects of the training decision on innovation. If we take endogenous training decision into account this feature allows the comparison of the results between the IV specification and the OLS specification. To compare the results from the linear probability models with more suitable models for binary choice variables we estimate probit models.

$$i_{jt} = \gamma_0 + \gamma_1 tr_{jt} + \sum_{k=2}^{K} \gamma_k x_{kjt} + e_{jt} \qquad (2.1)$$

Equation 2.1 is our basic estimation equation. We use 4 different measures for innovation (general innovation, product innovation, process innovation and patent applications). The variable of interest is the binary indicator for training participation of firm j at time t: tr_{jt}. We subsequently include a set of control variables. These control variables contain firm size, educational composition of a firms' workforce, competition measures (price and non-price competition)(Aghion, Bloom, Blundell, Griffith, & Howitt, 2005), lack of qualified workers, an indicator for foreign firm, and sector, year ,and regional dummies.

Endogenous training decision might be a potential source of bias in equation 2.1. This bias occurs if unobservable decisions influence both the training decision and the innovation output. Strategic management decisions for example might aim to foster innovation and simultaneously introduce the training of apprentices. To take this endogenous training decision into account we apply an instrumental variable strategy (Angrist & Krueger, 2001). As instrumental variable, we use the firm age and firms' language to measure training tradition.

Due to the panel structure of our data set we risk getting biased standard errors if do not correct for clustering at the firm level (Moulton, 1990). Therefore we use cluster-corrected standard errors for the basic equation and the instrumental variable equation.

[5] Due to missing observations for firms' R&D expenditures, we cannot include their lags into our model.

2.5 Results

2.5.1 OLS and Probit estimates

To test our hypothesis, we estimate equation 2.1 and use general innovation, product innovation, process innovation, and patent applications as dependent variables. According to our hypothesis we expect a positive impact on firm innovativeness of the firms' training participation. Table 2.2 shows the results for the estimation equation that includes the full set of control variables.

Column 1 of Table 2.2 shows the analysis of the influence on general innovation of a firms' decision to train apprentices. The results indicate that firms that participate in training have a 7.8 percentage points higher probability to innovate than firms not participating in VET. Columns 2 and 3 show the estimation results for product innovation and process innovation, respectively. Again, the decision to train apprentices is positively associated with product and process innovation. These coefficients are statistically significant at the 1 percent and the 5 percent level, respectively. The marginal effect of training is 7.2 percentage points for product innovation and 4.8 percentage points for process innovation. We also obtain a positive association of firms training participation and its patent applications. The marginal effect of training on patent applications is 6.7 percentage points.

Table 2.2 Linear probability model

Dependent variable	General innovation	Product innovation	Process innovation	Patent applications
Independent variable	Coef.	Coef.	Coef.	Coef.
Training firm	0.0782***	0.0715***	0.0475**	0.0666***
	(0.0220)	(0.0236)	(0.0240)	(0.0191)
Workforce education controls	yes			
Sector controls	yes			
Year controls	yes			
Region controls	yes			
Firm controls	yes			
Observations	2936			
R-squared	0.1192	0.1232	0.0719	0.1730

Note: Cluster robust standard errors in parenthesis (Cluster level: Firm).

* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

We re-estimate equation 2.1 using a Probit model to compare the estimation results from the linear probability model to a model that is more suitable for binary choice data. The marginal effects for the Probit estimates appear in Table A2.2 in the appendix. Compared to the results we report in Table 2.2, the marginal effects from the Probit model are similar in magnitude and direction. The estimates from the Probit model are highly significant for all innovation outcomes like those estimated in the linear probability model.

2.5.2 Instrumental variable estimates

As equation 2.1 does not account for potential endogenous training decision, we use an instrumental variable approach. Table 2.3 shows the estimation results of the first and second stage of a TSLS estimation.[6] In the first stage we regress the dummy that indicates firms' training participation on firm age and a set of control variables. Firm age is statistically significant at the 1 percent level (indicating a strong instrument) and shows a positive coefficient as expected. This result supports our expectation that older firms are more likely to offer dual-track VET compared to younger firms.

Table 2.3 Linear probability model, IV estimation (TSLS), instrument firm age

	First Stage	Second Stage			
Dependent Variable	Training firm	General Innovation	Product Innovation	Process Innovation	Patent Applications
Independent Variable	Coef.	Coef.	Coef.	Coef.	Coef.
Training firm		0.1946*	0.0794	0.1072	0.1727
		(0.1039)	(0.1194)	(0.1198)	(0.1091)
Firm Age	0.0021***				
	(0.0003)				
Workforce Education Controls	yes	yes			
Sector Controls	yes	yes			
Year Controls	yes	yes			
Region Controls	yes	yes			
Firm Controls	yes	yes			
Observations	2936	2936			
Centered R-squared	0.1090	0.1066	0.1232	0.0693	0.1595

Note: Cluster robust standard errors in parenthesis (Cluster level: Firm).

* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Columns 2-5 of Table 2.3 show the second stage results for the four innovation measures. These results deviate from the OLS and Probit estimates in the sense that their level of statistical significance is lower and the estimated coefficients are larger. Similar to the OLS

[6] Because a firm's training decision does not change considerably over time, we refrain from estimating a fixed effects model.

and Probit estimates the IV estimates indicate a positive effect of dual-track VET on the innovativeness of firms. This effect is statistically significant at the 10 percent level only for general innovation. For product and process innovation and for patents we do not obtain a statistically significant effect at conventional significance levels. The statistically significant estimate for general innovation is more than twice the size of the OLS estimate. The increase in the value of the coefficients might occur due to the importance of dual-track VET for the innovativeness of highly traditional firms. These firms might rely more heavily on the recruitment of workers with VET and qualifications that build upon VET than on firms that do not have a strong training tradition.

2.5.3 Robustness of instrumental variable estimates

As we cannot asses the validity of the instrument in the just-identified case presented in Table 2.3, we extend our IV approach by including instruments measuring training tradition based on firm-level language measures. Table 2.4 shows the estimation results of the first and second stage of a GMM estimation.[7] The first stage contains two instruments: firm age and a dummy that indicates German as firms' major language (German-speaking firm).

Table 2.4 shows statistically significant estimates at the 1 percent and 5 percent level, respectively and the expected signs for all of our instruments in the first stage. Again, as in Table 2.3, we find a positive coefficient for firm age. Furthermore, we find a positive coefficient for German-speaking firms. The positive coefficient indicates that German-speaking firms have a higher probability to participate in VET than French-speaking firms (the reference). To assess the strength of both instruments we test for the joint significance of both instruments in the first stage. Table 2.4 shows the F-statistic and the corresponding p-value. Both instruments are jointly significant at the 1 percent level, indicating strong instruments. Moreover a comparison of the F-statistic with the critical values reported in Stock and Yogo (2002) shows that the instruments are below the 10 percent maximal size threshold.[8]

[7] We present the results of a GMM estimation in this section as GMM is an efficient estimator if heteroscedasticity and clustering occurs. For the sake of comparability we include the TSLS estimates in the appendix (Table A2.3). We also report estimates from a limited information maximum likelihood (LIML) estimation (Table A2.4). LIML is more robust to weak instruments than the procedures mentioned above (Stock, Wight, & Yogo, 2002). The estimates of the LIML estimation are similar to those we report in Table 2.4.

[8] We follow Baum, Shaffer, and Stillman (2007) by comparing the F-statistic of the joint significance test for both instruments to the critical values reported in Stock and Yogo (2002) for the Cragg-Donald statistic. As we adjust the standard errors for clustering at the firm level, the i.i.d. assumption of the Cragg-Donald statistic is violated and the Kleibergen-Paap statistic is appropriate. In the single equation case, the Kleibergen-Paap rk F-statistic reduces to a F-statistic for the joint significance of the instruments in the first stage (Kleibergen &

A specification with two instruments and one endogenous variable allows us to test for overidentifying restrictions. As we use a GMM estimator that is efficient for clustering and heteroscedasticity, the Hansen J statistic and its corresponding p-value are appropriate to test the validity of our instruments. For the second stage specification shown in columns 2-4 of Table 2.4 we find p-values above 0.33. Thus the hypothesis that the instruments are valid cannot be rejected in these cases. Only in the specification shown in column 5 we can reject this hypothesis at the 10 percent level.

Table 2.4 Linear probability model, IV estimation (GMM), all instruments

	First Stage	Second Stage			
Dependent Variable	Training firm	General Innovation	Product Innovation	Process Innovation	Patent Applications
Independent Variable	Coef.	Coef.	Coef.	Coef.	Coef.
Training firm		0.1923**	0.1171	0.0698	0.0923
		(0.0978)	(0.1118)	(0.1135)	(0.0986)
Firm Age	0.0021***				
	(0.0003)				
German-Speaking Firm	0.2507**				
	(0.0979)				
Workforce Education Controls	yes	yes			
Sector Controls	yes	yes			
Year Controls	yes	yes			
Region Controls	yes	yes			
Firm Controls	yes	yes			
Observations	2936	2936			
F-Statistic (joint significance of instruments)	34.222				
p-value	0.000				
Hansen J Statistic		0.004	0.875	0.919	2.961
p-value		0.9476	0.3495	0.3376	0.0853
Centered R-squared	0.1132	0.1246	0.1216	0.0715	0.1721

Note: Cluster robust standard errors in parenthesis (Cluster level: Firm).
* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

The estimates of the second stage in Table 2.4 are in line with those in Table 2.3. Similarly to Table 2.3, the results in Table 2.4 show a positive impact of firms' participation in training on its innovativeness. This effect is statistically significant at the 5 percent level. For the other

Schaffer 2010). The comparison of the F-statistic to the critical values reported in Stock and Yogo (2002) shows that a 5 percent bias hypothesis is rejected in less than 10 percent of the time. This test result supports the strength of our instruments.

innovation outcomes we do not find statistically significant effects. The results in Table 2.3 and Table 2.4 indicate that our hypothesis cannot be rejected. With different sets of instruments we find support for a positive impact of participating in dual-track VET on the innovativeness of firms.

The use of firm age and firm language as instruments has its limitations. The population of older firms might be different from the population of younger firms. Older firms in the sample have undergone a selection process by market forces. Only those firms that survived this selection process are included in the sample. The population of younger firms in contrast might include firms that will not survive in the market in the next decade. As we do not have information on firms that exited the market, we cannot properly account for selectivity in this sample. Nevertheless, we make an attempt to run the IV estimation with the full set of instruments in a more homogeneous sample by excluding firms that are younger than 10. This restriction allows the exclusion of firms that are most likely to exit the market.

Table 2.5 Linear probability model for firms aged 10 and older, IV estimation (GMM), all instruments

	First Stage	Second Stage			
Dependent Variable	Training firm	General Innovation	Product Innovation	Process Innovation	Patent Applications
Independent Variable	Coef.	Coef.	Coef.	Coef.	Coef.
Training firm		0.1861*	0.0873	0.1081	0.1027
		(0.1110)	(0.1285)	(0.1269)	(0.1122)
Firm Age	0.0020***				
	(0.0003)				
German-Speaking Firm	0.2233**				
	(0.1019)				
Workforce Education Controls	yes	yes			
Sector Controls	yes	yes			
Year Controls	yes	yes			
Region Controls	yes	yes			
Firm Controls	yes	yes			
Observations	2764	2764			
F-Statistic (joint significance of instruments)	26.545				
p-value	0.000				
Hansen J Statistic		0.068	0.745	2.138	2.779
p-value		0.7936	0.3881	0.1437	0.0955
Centered R-squared	0.1105	0.1055	0.1223	0.0657	0.1643

Note: Cluster robust standard errors in parenthesis (Cluster level: Firm).

* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table 2.5 shows the GMM estimates of a specification that includes firm age and the German-speaking firm dummy as instruments in a sample that contains firms that are 10 or older. This table shows similar results compared to Table 2.4 where we use the entire sample. The first stage estimates in Table 2.5 show a positive effect of all instruments on firms' training participation at a similar statistical significance level reported in Table 2.5. Furthermore, the results in Table 2.5 support the second stage results in Table 2.3 and Table 2.4. We find a positive and statistically significant (at the 10 percent level) effect of firms participation in training on general innovation. Thus the estimation in a more homogeneous sample supports our hypothesis that dual-track VET has a positive impact on firms' innovativeness.

We repeat the estimation of the specification that uses the full set of instruments in samples that are less homogeneous. Therefore we generate an additional sample that includes firms that are 5 or older. Table A2.5 in the appendix show the estimation results. The results from this table do not contradict our hypothesis. In Table A2.5 we again find a positive effect of dual-track VET on general innovation and thus support for our hypothesis

2.5.4 Effects of training intensity

The impact of dual-track VET on innovativeness might not only depend on the participation in the VET system but also on the number of apprentices employed. Apprentices are one channel that contributes to the knowledge diffusion within the VET system. Firms that employ apprentices have to decide on the optimal number. The employment of apprentices comes along with their benefits for innovation but might also generate obstacles. Firms that employ an excessively large number of apprentices might lack sufficient resources to develop apprentices' skills through workplace training. In this case apprentices do not have the opportunity to apply the knowledge they gained from training curricula to real-world problems. Consequently, these firms can integrate the knowledge from the curricula at a lower rate than firms that foster the application of this knowledge during workplace training. We therefore expect that the relation between innovation and training intensity is inverted u-shaped.

To measure the association of training intensity with innovativeness, we include the number of apprentices employed to our estimation equation. As we expect an inverted u-shaped functional form, we include the squared number of apprentices in our specification. Table 2.6 shows the estimation results for specifications that include the full set of control variables. Dual-track VET is positively associated with all innovation measures. Furthermore, the coefficients for the training intensity measures show an inverted u-shaped relationship between the number of apprentices and innovation outcomes. This relation is statistically significant for general innovation, product innovation and patent applications. A calculation of the turning points for all specification yields values that exceed 400. These large values should be interpreted with caution as the estimates might be driven by large firms in the sample. We refrain from an exact calculation of the turning points for each industry as we are more interested in the general relation between training intensity and innovation[9].

Table 2.6 Linear probability model including training intensity measures

Dependent Variable	General Innovation	Product Innovation	Process Innovation	Patent Applications
Independent Variable	Coef.	Coef.	Coef.	Coef.
Training firm	0.0699***	0.0603***	0.0414	0.0501***
	(0.0224)	(0.0243)	(0.0245)	(0.0195)
Training Intensity	0.0014**	0.0019**	0.0010	0.0027***
	(0.0006)	(0.0008)	(0.0007)	(0.0009)
Training intensity squared	-0.0017*	-0.0021**	-0.0017	-0.0034***
	(0.0009)	(0.0011)	(0.0013)	(0.0010)
Workforce Education Controls	yes	yes	yes	yes
Sector Controls	yes	yes	yes	yes
Year Controls	yes	yes	yes	yes
Region Controls	yes	yes	yes	yes
Firm Controls	yes	yes	yes	yes
Observations	2936	2936	2936	2936
R-squared	0.1208	0.1255	0.0726	0.1810

Note: Cluster robust standard errors in parenthesis (Cluster level: Firm).
* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.
Coefficients and Standard Errors for the variable Training intensity squared are multiplied by 1000.

The results in Table 2.6 show that after controlling for training intensity a positive association of training participation remains. Compared to training intensity, the coefficient of training participation is up to 50 times larger (in the case of general innovation) than the coefficient for training intensity. This result shows that firms experience an innovation premium from participating in training regardless their training intensity. Due to the lack of a sufficient number of instrumental variables, we cannot show that this relationship is a causal one.

[9] The large turning point of 400 should not be interpreted in the way that firms should hire more apprentices to achieve optimal innovativeness. Instead it should show in a general manner that firms might enhance their innovativeness by increasing training intensity.

Nevertheless, the results are in line with our theoretical expectations and support our hypothesis.

2.5.5 Effects of firm size

The size of a firm reflects the availability of resources that can be devoted to R&D and thus lead to innovation (Acs & Audretsch, 1988). Larger firms are expected to have more resources that can be used for R&D than smaller firms. Thus, we expect firms of different sizes to benefit differently from the knowledge diffusion of dual-track VET. In terms of innovativeness we expect larger firms to benefit less from dual-track VET as they foster the inclusion of their latest knowledge in training curricula. Smaller firms might not have access to the latest technologies and therefore benefit strongly from knowledge the curricula contains.

Table 2.7 Linear probability model including firm size-interaction with training status

Dependent Variable	General Innovation	Product Innovation	Process Innovation	Patent Applications
Independent Variable	Coef.	Coef.	Coef.	Coef.
Training firm	0.0835***	0.0760***	0.0574**	0.0802***
	(0.0233)	(0.0247)	(0.0256)	(0.0198)
Firm size	0.0001	0.0001	0.0003*	0.0003***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Training firm*Firm size	-0.0001	-0.0001	-0.0002	-0.0003**
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Workforce Education Controls	yes	yes	yes	yes
Sector Controls	yes	yes	yes	yes
Year Controls	yes	yes	yes	yes
Region Controls	yes	yes	yes	yes
Firm Controls	yes	yes	yes	yes
Observations	2936	2936	2936	2936
R-squared	0.1194	0.1234	0.0726	0.1749

Note: Cluster robust standard errors in parenthesis (Cluster level: Firm).
* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

To obtain estimates for the relation of firm size and firms' training participation, we augment our estimation equation by including the interaction of firm size and training participation. Table 2.7 shows the results of this estimation including the full set of instruments. Participating in dual-track VET is still positively associated with all innovation measures. The interaction of dual-track VET and firm size is negatively associated with innovation. These estimates are not statistically significant at conventional levels. Only for patent applications we obtain a statistically significant estimate at the 5 percent level.

This robustness check shows that the positive association of dual-track VET and innovation remains if we extend the analysis by including a dual-track VET and firm size interaction. By taking the magnitude of this association into account, larger firms do not gain as much from participating in VET as smaller firms do.

2.6 Discussion

In this chapter we analyze the impact of dual-track VET on innovation at the firm level. We argue that institutions in secondary education function as a knowledge diffusion mechanism. We identify the training curricula of dual-track VET as a diffusion channel. Thus we hypothesize that firms participating in dual-track VET are more innovative than firms not participating in such training. We use data from a large Swiss innovation survey to test our hypothesis. Our estimation results support that dual-track VET has a positive impact on innovation at the firm level. We find a positive and statistically significant association of dual-track VET with general innovation, product innovation, process innovation and patent applications. This positive association remains after controlling for firms' training intensity. If we take the endogeneity of the training decision into account, the results show a positive and statistically significant effect of dual-track VET on general innovation.

Our empirical results are in line with our hypothesis. Due to the high involvement of employer association, employee association and the government in the creation and revision of VET curricula, new knowledge enters the VET system. Apprentices learn this knowledge in vocational schools and apply it during workplace training. Firms participate in this system by providing dual-track VET and thus have access to an additional knowledge source. This knowledge source accelerates the adaptation of new technologies and results in a higher innovative output compared to firms that do not participate in the system.

We find support for our hypothesized effect throughout several empirical approaches that treat firms' participation dual- track VET as either exogenous or endogenous. We use firms' training tradition as an instrument for training participation and take two approaches to operationalize training tradition. In the first approach we argue that firms' age influences its training tradition. Older firms had more time to establish their training tradition than younger firms. As dual-track VET experienced a boom in the mid of the last century, we expect that it became part of an older firms' training tradition. In the second approach we use a firms' language to operationalize training tradition. In Switzerland firms training participation differs by linguistic region. In the German-speaking part of Switzerland firms offer dual-track VET more frequently than in the French or Italian-speaking part. We argue that besides the regional differences of training participation, language reflects firms' training tradition. Therefore, we focus our analysis on the German-speaking part and identify firms that have a different language. We expect these firms to have a lower probability to participate in training than their German-speaking counterparts. Our analyses show that the instruments influence training participation in the expected way. Older firms and German-speaking firms have a higher probability to train. The results from our IV approach are highly robust throughout different specifications. Also when we consider that the sample consists of a selection of firms that survived and exclude those that are most likely to exit, our IV results remain stable.

The use of firm age and firm language as instruments for training participation has its limitations. Although our test statistics support the strength and the validity of the instruments, the exogeneity of the instruments might not be comparable with the standards of a randomized experiment. Firm language might enable firms to access certain innovation networks. German-speaking firms might access German-speaking networks easier than French-speaking networks. The association of firms with different networks might influence their innovativeness. To reduce this source of bias, we restrict our sample to the German-speaking part of Switzerland. Nevertheless French-speaking firms might have a different network structure than their German-speaking counterparts resulting in different innovations. Firm age might represent selectivity in the sample we use for our analyses. If older firms represent a selection of firms that are more innovative our results might be biased. Because we lack information on firms that exited the market, we cannot test for this sort of bias. Despite these limitations we find a highly robust and positive coefficient of training participation for general innovation, a result that indicates at least a strong association of training participation and firms' innovativeness.

Further analyses focus on training intensity and firm size. After controlling for training intensity we can show that training participation is still positively associated with innovation. This association indicates that the participation itself is beneficial for firms. The magnitude of the influence of training intensity on innovation is small compared to the coefficient for training participation. Thus, firms might not necessarily have a high training intensity to benefit from the knowledge included in the training curricula. We furthermore investigate whether a high training intensity boosts firms' innovativeness. Our results show an inverted u-shaped relation of training intensity and innovation. An extensive training intensity might therefore reduce firms' gains from training participation.

We lastly investigate the influence of firm size on firms' gains from training participation. We expect larger firms to have comparably smaller benefit from participating in dual-track VET than smaller firms. Large firms actively participate in the revision of curricula and suggest potential directions for curricula development based on the latest technology they use. Our results show a negative association for the interaction of firm size and training participation and that supports our expectation.

Our results have several theoretical and practical implications. Secondary vocational education contributes to innovation in highly developed countries like Switzerland. This finding contradicts standard models by Krueger and Kumar (2004a, 2004b) and Aghion and Howitt (2006). From the perspective of these models, vocational education does not have the potential to contribute to innovation in a highly innovative environment. As vocational education differs between countries in terms of generality and quality, recent models could consider both factors of vocational education.

By identifying and analyzing knowledge diffusing mechanisms in the Swiss VET system we highlight the importance of knowledge diffusion for innovativeness. This finding is of particular importance of policy makers and professional organizations. To ensure a constant inflow of new technologies into VET curricula, the cooperation of different stakeholders in the curriculum setting process is necessary. Especially the cooperation with stakeholders that determine the use of new technologies in a certain occupation (e.g., customers, suppliers, research institutions) is important for the definition of future contents of the curricula. These stakeholders might not necessarily operate in a similar industry but their expertise might help to adapt faster to technological changes.

In limiting our analysis to the curriculum and its application as a central mechanism for knowledge diffusion, we do not want to exclude other potential mechanisms. Possible channels for knowledge diffusion are VET teachers (Backes-Gellner, 1996) and the utilization of inter-company courses. Teachers in dual-track VET function as an interface between secondary vocational education, tertiary vocational education and practice. Teachers in vocational schools and inter-company courses have both, a completed tertiary education and practical experience in their occupation. Some teachers still work in a firm and teach part-time. Moreover most of the teachers teach at the secondary and tertiary level. Thus, teachers in VET receive multiple information from different sources. On the one hand they might receive information on technological developments from the firm they work for. On the other hand they know the curricula from tertiary vocational education (Professional Education and Training (PET)). Whenever changes in the production technology or in the PET curricula occur, VET teachers can integrate this new knowledge in their own teaching. The high qualification of VET teachers and their access to multiple knowledge sources facilitates the diffusion of new knowledge within the VET system.

Knowledge diffusion could also occur in inter-company courses. As several inter-company courses take place in teaching centers of professional organizations and some teaching centers are connected to research institutions, knowledge from the latest research can be integrated in inter-company courses. It would be interesting to see how these diffusion mechanisms must be configured and combined with the curriculum to foster innovation. We leave the analysis of further diffusion mechanisms and their interactions as a theme for further research.

In this chapter we show that dual-track VET has a positive impact on the innovativeness of firms. Building upon this finding, we analyze in the next chapter how firms combine and manage workers with different educational backgrounds to achieve superior innovation performance.

Appendix

Figure A2.1 Distribution of the founding year

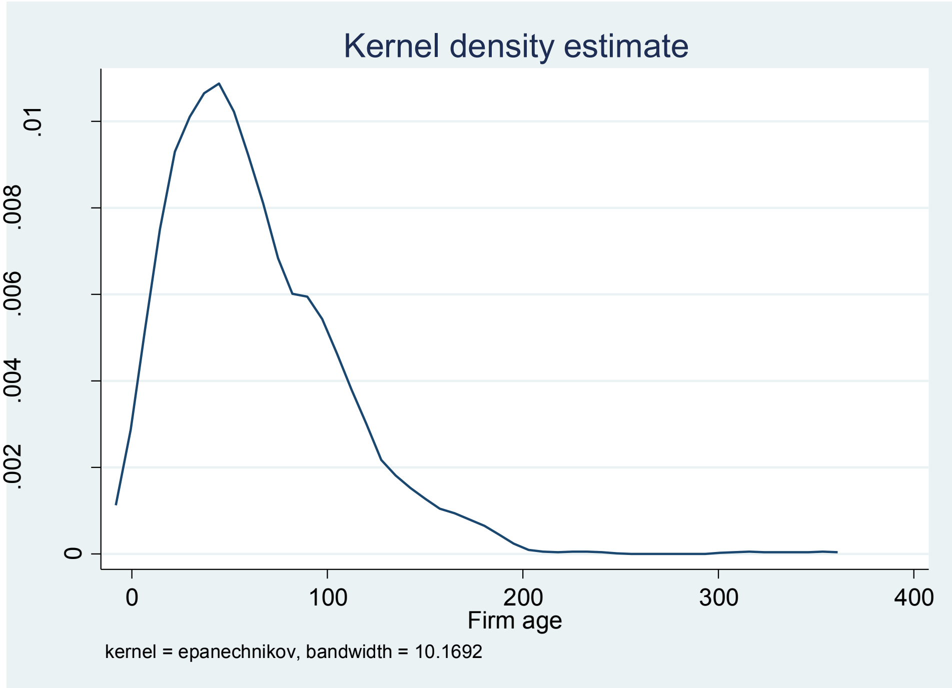

Figure A2.2 Firm age and apprenticeship training

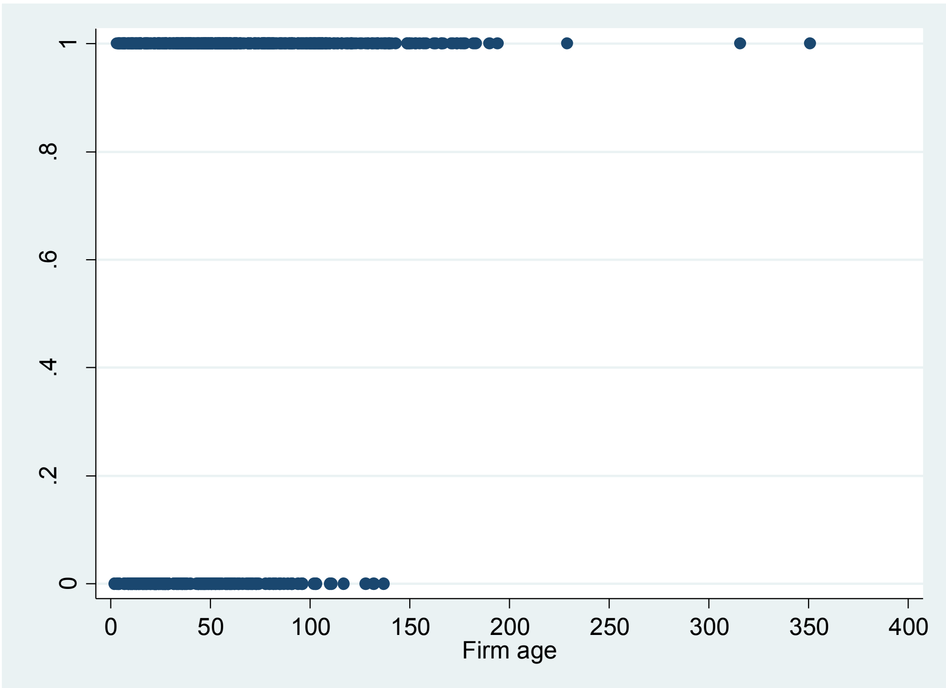

Table A2.1 Correlations between dependent variables, endogenous variables and instruments

	1.	2.	3.	4.	5.	6.	7.
1. General innovation	1.000						
2. Product innovation	0.808	1.000					
	(0.000)						
3. Process innovation	0.640	0.408	1.000				
	(0.000)	(0.000)					
4. Patent applications	0.300	0.352	0.183	1.000			
	(0.000)	(0.000)	(0.000)				
5. Training firm	0.072	0.060	0.044	0.073	1.000		
	(0.000)	(0.001)	(0.017)	(0.000)			
6. Firm age	0.033	0.012	0.023	0.033	0.227	1.000	
	(0.074)	(0.527)	(0.213)	(0.079)	(0.000)		
7. German-Speaking firm	0.014	0.031	-0.004	-0.005	0.070	0.007	1.000
	(0.450)	(0.097)	(0.842)	(0.773)	(0.000)	(0.721)	

Note: Significance levels in parentheses.

Table A2.2 Probit model

Dependent variable	General innovation	Product innovation	Process innovation	Patent applications
Independent variable	Marg. Eff.	Marg. Eff.	Marg. Eff.	Marg. Eff.
Apprenticeship-training firm	0.0726***	0.0683***	0.0447*	0.0717***
	(0.0208)	(0.0229)	(0.0240)	(0.0200)
Workforce education controls	yes			
Sector controls	yes			
Year controls	yes			
Region controls	yes			
Firm controls	yes			
Observations	2936			
Pseudo R-squared	0.1085	0.0997	0.0547	0.2015

Note: Cluster robust standard errors in parenthesis (Cluster level: Firm).

* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table A2.3 Linear probability model, IV estimation (TSLS)

	First Stage	Second Stage			
Dependent Variable	Training firm	General Innovation	Product Innovation	Process Innovation	Patent Applications
Independent Variable	Coef.	Coef.	Coef.	Coef.	Coef.
Training firm		0.1926**	0.1150	0.0705	0.1228
		(0.0978)	(0.1118)	(0.1135)	(0.1001)
Firm Age	0.0021***				
	(0.0003)				
German-Speaking Firm	0.2507**				
	(0.0979)				
Workforce Education Controls	yes	yes			
Sector Controls	yes	yes			
Year Controls	yes	yes			
Region Controls	yes	yes			
Firm Controls	yes	yes			
Observations	2936	2936			
F-Statistic (joint significance of instruments)	34.222				
p-value	0.000				
Hansen J Statistic		0.004	0.875	0.919	2.961
p-value		0.9476	0.3495	0.3376	0.0853
Centered R-squared	0.1132	0.1070	0.1217	0.0715	0.1692

Note: Cluster robust standard errors in parenthesis (Cluster level: Firm).

* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table A2.4 Linear probability model, IV estimation (LIML)

	First Stage	Second Stage			
Dependent Variable	Training firm	General Innovation	Product Innovation	Process Innovation	Patent Applications
Independent Variable	Coef.	Coef.	Coef.	Coef.	Coef.
Training firm		0.1925**	0.1155	0.0707	0.1245
		(0.0978)	(0.1129)	(0.1145)	(0.1031)
Firm Age	0.0021***				
	(0.0003)				
German-Speaking Firm	0.2507**				
	(0.0979)				
Workforce Education Controls	yes	yes			
Sector Controls	yes	yes			
Year Controls	yes	yes			
Region Controls	yes	yes			
Firm Controls	yes	yes			
Observations	2936	2936			
F-Statistic (joint significance of instruments)	34.222				
p-value	0.000				
Hansen J Statistic		0.004	0.875	0.919	2.958
p-value		0.9476	0.3495	0.3376	0.0853
Centered R-squared	0.1132	0.1070	0.1217	0.0715	0.1690

Note: Cluster robust standard errors in parenthesis (Cluster level: Firm).

* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table A2.5 GMM Estimation for firms aged 5 years or older

	First Stage	Second Stage			
Dependent Variable	Training firm	General Innovation	Product Innovation	Process Innovation	Patent Applications
Independent Variable	Coef.	Coef.	Coef.	Coef.	Coef.
Training firm		0.1856*	0.0888	0.0659	0.07922
		(0.1004)	(0.1157)	(0.1163)	(0.1019)
Firm Age	0.0021***				
	(0.0003)				
German-Speaking Firm	0.2402**				
	(0.0990)				
Workforce Education Controls	yes	yes			
Sector Controls	yes	yes			
Year Controls	yes	yes			
Region Controls	yes	yes			
Firm Controls	yes	yes			
Observations	2882	2882			
F-Statistic (joint significance of instruments)	32.143				
p-value	0.000				
Hansen J Statistic		0.060	0.752	1.315	2.618
p-value		0.8064	0.3859	0.2516	0.1056
Centered R-squared	0.1135	0.1065	0.1238	0.0703	0.1743

Note: Cluster robust standard errors in parenthesis (Cluster level: Firm).

* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Chapter 3 How to combine human resource management systems and human capital pools to achieve superior innovation performance

(A (former) version is also available as: "How to combine human resource management systems and human capital pools to achieve superior innovation performance." Swiss Leading House Working Paper no. 89 (2013). By Christian Rupietta and Uschi Backes-Gellner.)

3.1 Introduction

Firms generate innovations through recombinations of existing knowledge sources (Kogut & Zander, 1992). The quality and quantity of these recombinations depend on a firm's stock and flow of knowledge. The human capital of employees is an important part of a firm's knowledge stock, as it contains knowledge and skills relevant for innovation (Wright, McMahan, & McWilliams, 1994; Wright et al., 2001). The human resource management (HRM) system comprises human resource practices that affect both the organization of work and workers' behavior, thereby initiating and regulating the knowledge flow between workers (Wright et al., 1994; Wright et al., 2001). Both human capital pools and HRM systems build on the notion that complementarities exist between different types and levels of skills and different HRM practices, respectively. Wright et al. (1994) and Wright et al. (2001) point out that complementarities also occur between a firm's human capital pool and HRM system, and argue for an integrated perspective.

Although the theoretical HR literature combines human capital pools and HRM systems,[10] these approaches remain neglected in the empirical innovation literature. Empirical studies explain innovation from either the HRM or human capital perspective. Those taking the HRM perspective analyze the relationship between single HRM practices (e.g., Laursen, 2002; Laursen & Foss, 2003) or HRM systems (e.g., Delery & Doty, 1996; Guest, Conway, & Dewe, 2004) and innovation. Studies taking the human capital perspective focus on average human capital (e.g., Galunic & Rodan, 1998; Subramaniam & Youndt, 2005) or firms' diversity in human capital (e.g., Østergaard, Timmermans, & Kristinsson, 2011). Although a recent literature stream links human capital and HRM (e.g., Cabello-Medina, Lopez-Cabrales,

[10] Miles and Snow's (1984) typology contains management practices and practices that affect workforce skills. Lepak and Snell (1999) distinguish between the value and uniqueness of human capital, arguing that the applicability of certain management practices depends on workers' skills. Typologies with a similar approach (i.e., using practices that affect workforces skills instead of dealing with them directly) are proposed by Kerr and Slocum, Jr (1987); Osterman (1994) and Sonnenfeld and Peiperl (1988). Wright et al. (2001) identify knowledge stocks (human capital) and knowledge flows (workers' behavior resulting from a firm's HRM system) as parts of what they call an "HR system."

& Valle-Cabrera, 2011; De Winne & Sels, 2010), it focuses on single or moderating effects and neglects multiple complex complementarities between human capital and HRM. Thus, for the joint influence of a firm's human capital pool and HRM system on innovation, a large gap between theorizing (i.e., using a configurational approach) and analyzing (i.e., generally using contingency approaches) remains.

This study fills this gap in the literature in two ways: First, we follow Wright et al. (2001) by arguing that a firm's human capital pool resembles a firm's knowledge stock and that the application of a system of HRM practices that facilitate worker interaction regulates the knowledge flow. As our focus is on knowledge exchange, we analyze only those mechanisms that facilitate knowledge exchange within the firm. Our analysis shows complementarities both within and between the two factors. We thus reformulate the Wright et al. (2001) model to a knowledge creation (KC) system that contains stock and flow components and underlies configurational theory.

Second, we analyze the KC system by applying fuzzy set qualitative comparative analysis (fsQCA) (Ragin, 2008). This method helps us to overcome the drawbacks of other methods (e.g., regression analysis, cluster analysis, deviation score analysis) used for analyzing complex systems (Fiss, 2007). More specifically, fsQCA can cope with equifinality and causal complexity (Fiss, 2007), two major properties of configurational theory (Doty, Glick, & Huber, 1993). By applying fsQCA to an analysis of a firm's KC system, we can identify multiple configurations. From our results we derive a taxonomy that refines HR theory and typologies.

For our analysis we use data from the Swiss manufacturing sector. This data set contains measures for a firm's human capital pool (i.e., different percentages of workers with similar educational degrees), a firm's HRM system (i.e., teamwork, job rotation, and empowerment), and allows us to include firm size and industry dynamism. The dynamism of a firm's environment is an important factor influencing not only firm innovativeness but also the educational composition of the workforce and the applicability of HRM practices (Datta, Guthrie, & Wright, 2005). We use the sales percentage of highly improved products as a measure for innovation.

The results of our analysis reveal multiple configurations of the KC system, configurations best described as a taxonomy similar to the management system typology proposed by Burns and Stalker (1961). We identify four configurations, two of which are strongly related to what they call the “mechanistic” and “organic” forms. At the one extreme we find the mechanistic form, i.e., we find low industry dynamism combined with single-skill concentration and a disregard for HRM practices. At the other extreme, we find the organic form, i.e., we find high industry dynamism combined with a highly qualified and diversified workforce and a strong focus on empowerment. The two remaining configurations constitute hybrid forms located in a highly dynamic environment relying either on vocational skill diversity or on organizational learning.

Our analysis of the KC system contributes to the HR and innovation literature in two ways. First, we show the existence of multiple strategies for superior innovation performance. These strategies differ with regard to their focus (either human capital or HRM) and highly depend on industrial dynamism. Our taxonomy also has further implications for the refinement of existing typologies. Second, we identify hybrid configurations that are either stable forms located in the continuum between the two (mechanistic and organic) extremes, or they are snapshots of firms that change their KC system. For example, these hybrid forms could support firms in performing transitions resulting to cope with industrial dynamism.

3.2 Theoretical and empirical literature

Innovation is a complex phenomenon that results from a recombination of knowledge sources (Kogut & Zander, 1992). To achieve knowledge recombinations, firms require a knowledge stock that contains innovation relevant knowledge and practices that induce knowledge flow. Firms induce knowledge flow by using HRM systems that influence work organization and workers’ behavior, thereby creating an environment for cooperation and interaction (Schuler & Jackson, 1987; Wright et al., 2001). Moreover, by selecting highly skilled workers, firms build their knowledge stock (Boxall, 1996; Wright et al., 2001).

3.2.1 Complementarities within and between HRM system and human capital pool

Complementarities exist in HRM systems and in human capital pools. The configurational approach in HRM theory expects these complementarities to occur in multiple and non-linear interactions between HRM practices (Delery & Doty, 1996). Such HRM systems must be internally consistent and externally aligned with the firms’ strategy (Becker & Huselid, 1998). Typologies such as those derived by Miles and Snow (1984) integrate an internally consistent HRM system into a firm’s strategy and business environment, and expect similar outcomes for their specific ideal types.[11] Thus different configurations of an HRM system can be equally effective in generating a certain output (Delery & Doty, 1996; Doty & Glick, 1994). Such a system of practices might enhance knowledge exchange not only through changes in the organization of work (e.g., team work or job rotation) (Collins & Smith, 2006; Smith, Collins, & Clark, 2005) but also through influencing workers' behavior (e.g., empowerment) (Schuler & Jackson, 1987).

Grant and Hayton (2011) argue that, like complex complementarities in an HRM system, complementarities occur between differently skilled individuals. As different skills originate from differences in education, the educational composition of a firm's workforce affects the amount of complementarities between workers. Because education can differ in terms of level, type, or field, complementarities within a firm's human capital pool can be highly complex. Thus a human capital pool and an HRM system share a similar degree of complexity.

Although the integration of human capital and HRM into a single system is a well-established concept, little is known about either the complementarities within such a system or their implications for knowledge exchange. Researchers investigate knowledge exchange mainly by analyzing either HRM practices (e.g., internal promotion, teamwork, job rotation) (e.g., Collins & Smith, 2006) or human capital (e.g., skill level, skill diversity) (e.g., Østergaard et al., 2011). The following subsection focuses on the analysis of such complementarities and their implications for knowledge exchange.

3.2.2 Complementarities and knowledge exchange

Complementarities within and between human capital pools and HRM systems influence the innovativeness of firms.[12] We first investigate how complementarities within an HRM system and within a human capital pool influence knowledge exchange, and then analyze complementarities between both factors.

In an HRM system, synergies occur from the joint application of practices that reinforce one another. For example, one important feature of teamwork is the interaction of team members

[11] Although Burns & Stalker (1961) typology has strong implications for innovation, HRM and the skills of a firm's workforce, we do not elaborate on it because it constitutes a generic management system, not an explicit HR typology.

[12] Research on complementarities within and between a firm's human capital pool and HRM system has a long tradition in the HR literature. Innovation as one outcome of these complementarities has gained popularity during the last two decades. More established outcomes are firms' financial performance, productivity, and turnover (e.g., Becker & Huselid, 1998; Becker & Gerhart, 1996; Huselid, 1995; Ichniowski, Shaw & Prennushi, 1997).

and their knowledge exchange. (As the HRM system consists of multiple practices, we assume that more complex complementarities occur than those shown in our example.) Differences in knowledge, functions, or experience among team members, who therefore might lack a common language, might impede knowledge exchange (Dougherty, 1992; Grant, 1996b). To overcome this problem, team members can improve knowledge exchange by creating homogenous subgroups that allow their members to find a common ground (Crawford & Lepine, 2013). Although subgroups facilitate interactions at the subgroup level, the overall effectiveness of the team depends on collaboration between subgroups (Carton & Cummings, 2012).

At this point the combined application of teamwork and job rotation can bridge differences between subgroups. Collins and Smith (2006) argue that job rotation enhances the cross-functional and cross-divisional diffusion of knowledge. By implementing job rotation, firms increase the likelihood that workers have diverse knowledge and can cope with different terminologies. These workers can adopt integrating roles in their team (Crawford & Lepine, 2013) and align the knowledge of different subgroups. Thus a combined application of HRM practices might help the firm to overcome the weaknesses of single practices and generate synergies that leverage knowledge exchange. We therefore expect that, to implement teamwork successfully, a highly specialized workforce needs to bridge differences between subgroups by applying job rotation.

As with HRM systems, complementarities can occur between different types and levels of workers' education, e.g., differences in education mean that workers have different knowledge. Grant (1996a) argues that "sophisticated common knowledge" enhances the communication of specialized knowledge. If the difference between specialized knowledge and common knowledge is large, workers must reduce their specialized knowledge to common knowledge, thereby losing information during the simplification process (Grant, 1996a). Thus complementarities between different types and levels of knowledge simplify knowledge exchange.

Complementarities exist not only within a firm's human capital pool and within its HRM system but also between them. For example, by applying teamwork and employing a workforce that shares "sophisticated common knowledge," a firm shapes an environment that enhances the collaboration among workers and capitalizes on what they have in common. For example, workers who completed the same vocational education and training program in a given occupation and continued their education with different professional education and training programs have common sophisticated knowledge. In such cases formal practices that improve cross-functional and cross-divisional knowledge sharing (e.g., job rotation) might not be necessary, because workers can easily integrate knowledge from their team members. We therefore expect that a workforce that contains different levels and types of skills but shares sophisticated common knowledge can successfully implement teamwork without introducing job rotation.

We argue that firms' abilities to exchange knowledge depend on complementarities within and between both its human capital pool and its HRM system. We therefore argue that knowledge exchange and thus knowledge creation (KC) depend on a system that has two components: knowledge stock (Human capital) and knowledge flow (Worker interaction induced by the HRM system). The structure of a KC system is similar to what Wright et al. (2001) call an "HR system." As we focus on the properties of the KC system in generating innovation, we use the term "knowledge creation" system.

3.2.3 Empirical approaches and their theoretical foundation

Empirical studies that focus on a system of human capital and HRM when analyzing innovation are virtually non-existent. In their review of empirical studies on the link between HRM and organizational outcomes, Jiang, Lepak, Jia, and Bear (2012) show that most studies do not consider innovation an outcome. Very few studies that investigate innovation examine both human capital and HRM. This subsection describes the empirical approaches of these studies.

De Winne and Sels (2010) investigate the influence of human capital and HRM on innovation by taking a contingency approach. They argue that the level of the workers' human capital moderates the impact of HRM practices on innovation and expect the impact of HRM practices to increase with the level of human capital. For their empirical analysis they use the percentage of workers who have completed a bachelor's degree or higher as a measure of human capital. They measure HRM practices by counting the practices applied. After applying path analysis, they show that workers' human capital moderates the impact of HRM practices on innovation.

Cabello-Medina et al. (2011) take a different approach by arguing that HRM practices affect human and social capital and that both types of capital affect innovation. In contrast to De Winne and Sels (2010), they do not include moderating effects in their model; instead, they distinguish between different functions of human capital (i.e., uniqueness and value). Cabello-Medina et al. (2011) operationalize the value of human capital with a 5-item scale and operationalize the uniqueness of human capital with a single variable. To measure HRM practices, they distinguish between practices related to development, selection, incentives, and empowerment (all scales). The results of their structural equation model show three positive effects: that of human capital on innovation, that of developmental HRM practices on the value of human capital, and that of empowerment on the uniqueness of human capital.

Two additional studies are located in the context of the influence of human capital and HRM on innovation. Bornay-Barrachina et al. (2012) expect human capital to mediate the relationship of employment relations and innovation. Their analyses support their hypothesis. Moreover, Lopez-Cabrales, Pérez-Luno, and Valle Cabrera (2009) hypothesize that knowledge is a moderator between HRM practices and firms' innovation output. Distinguishing between uniqueness and value of knowledge, they show that unique knowledge mediates the relationship between both collaborative HRM practices and innovation, and that knowledge-based HRM practices positively influence innovation.

All of these empirical studies investigate the influence of human capital and HRM on innovation from either a universalistic or contingency perspective. Only De Winne and Sels (2010) use the contingency approach in their empirical analysis.[13] Thus the configurational approach that combines a firm's human capital pool and HRM system remains under-investigated in the empirical literature. According to Doty et al. (1993) and Doty and Glick (1994), analyses that consider the configurational approach must take equifinality and complex synergies into account. These properties of configurational theory challenge current empirical approaches (e.g., regression analysis, cluster analysis or deviation score analysis), because most of them cannot handle either equifinality or complex synergies (Fiss, 2007).

3.3 Empirical analysis

Our theoretical model of a KC system is based on configurational theory. We therefore use fuzzy set qualitative comparative analysis (fsQCA), a method that takes several properties of configurational theory (e.g., equifinality and causal complexity) into account (Fiss, 2007, 2011). This method allows us to identify several complex KC system configurations that explain innovativeness.

[13] Although Bornay-Barrachina, De la Rosa-Navarro, López-Cabrales, and Valle-Cabrera (2012) also consider moderating effects, they focus on employment relations and do not deal directly with HRM practices.

For the measurement of innovation, we focus on incremental innovation. Compared to other innovation types, incremental innovation has the highest alignment with the KC system we have described. To generate innovation, the KC system builds upon the use of a given knowledge stock. Because incremental innovation relies more on the existing knowledge sources of a firm than on new knowledge entering the firm (Henderson & Clark, 1990; Subramaniam & Youndt, 2005), our KC system is consistent with the determinants of incremental innovation.

A firm's innovativeness depends not only on internal factors but also on external factors such as environmental velocity (McCarthy, Lawrence, Wixted, & Gordon, 2010). ”Environmental velocity” refers to factors related to industry dynamism, turbulence, and hypterturbulence (McCarthy et al., 2010), factors also known to influence the configuration of the KC system. Datta et al. (2005) argue that a firm's industrial environment influences skill requirements and information processing needs, and expect, for example, that a dynamic environment increases both factors. We therefore consider a firm's industrial environment in our empirical approach.

3.3.1 Data

For our empirical analysis we use the 2005 wave of the Innovation Survey collected by the Swiss Economic Institute (KOF). This data set is representative for the Swiss firm populations in the manufacturing, construction, and service sectors. It also contains detailed information on a firm's innovativeness, the educational composition of a firm's workforce, and the HRM practices that a firm applies.

We restrict our sample to the manufacturing sector for the following two reasons: First, innovation processes tend to differ between the manufacturing and service sectors (Ettlie & Rosenthal, 2011; Hollenstein, 2003), and we therefore refrain from analyzing them jointly. Second, Arvanitis and Hollenstein (2001) and Hollenstein (1996, 2003) show that the Swiss manufacturing sector is based primarily on incremental innovations, whereas the service sector does not have such a strong orientation towards incremental innovations. As our KC system is consistent with the determinants of incremental innovation, we focus on the manufacturing sector.

Given the high market orientation of incremental innovation in Swiss manufacturing (Hollenstein, 1996), we select a measure that captures this pattern. Market-oriented innovation measures relate innovation output to financial performance measures such as sales or revenue (Arnold, Fang, & Palmatier, 2011; Hollenstein, 1996). To obtain a measure for firms' incremental innovation performance, we use the sales percentage of highly improved products (Atuahene-Gima, 2005; Henard & McFadyen, 2012).

As measures for human capital pool and HRM system, we select both the educational composition of the workforce and the HRM practices that regulate knowledge flow. The KOF collects information on the educational composition of the workforce by categorizing workers into 5 groups and calculating their percentage of the total workforce. This categorization distinguishes among workers with university degrees, workers with degrees from professional education and training (PET), workers with degrees from dual-track vocational education and training (VET), workers with degrees from lower-secondary schooling, and apprentices.[14] For our analysis we focus on educational degrees higher or equal to dual-track VET. As workers with completed lower-secondary schooling do not have additional occupation-specific knowledge, they cannot contribute to a firm's knowledge stock. Moreover, apprentices are a source of external knowledge inflow from the VET system (Rupietta & Backes-Gellner, 2012) not an internal source of knowledge. We thus exclude these two groups from our analysis.

We gather information on HRM practices from the items measuring the application of teamwork, job rotation, and empowerment (the distribution of decision-making responsibilities between worker and supervisor). The items on teamwork and job rotation are measured by two binary items. The KOF uses 7 items to measure empowerment. For each item, the KOF uses a 5-point Likert scale ranging from 1 (the worker has all the decision-making responsibilities) to 5 (the supervisor has all the decision-making responsibilities). The 7 items cover information such as the sequencing of work, customer relations, and customer complaints (see Table 3.1 for the full list). We also include firm size, measured by the number of employees.

[14] Dual-track VET constitutes 3-to-4-year training programs at the upper secondary level. These programs combine intense workplace training with vocational schooling. About two thirds of a cohort continues with dual-track VET after having completed lower secondary education. PET constitutes a variety of programs at the tertiary level. A large majority of students starting a PET program have already completed VET. Like VET, PET, combines practical and theoretical education.

Table 3.1 Descriptive Statistics

	Traditional manufacturing					High tech manufacturing				
Variables	Obs.	Mean	Std. dev.	Min.	Max.	Obs.	Mean	Std. dev.	Min.	Max.
Uncalibrated										
Sales share strongly improved products	213	14.827	18.010	0	100	248	23.613	20.564	0	100
Human capital pool (large share of workers with:)										
University degree	213	3.061	5.123	0	54	248	6.750	7.959	0	50
PET degree	213	10.291	8.311	0	50	248	17.403	12.179	0	76
VET degree	213	41.263	20.515	0	90	248	45.758	18.029	4	86
HRM system										
Teamwork	213	0.742	0.439	0	1	248	0.839	0.369	0	1
Job rotation	213	0.296	0.457	0	1	248	0.246	0.432	0	1
Work pace	213	3.282	0.737	1	5	248	3.206	0.775	1	5
Sequencing	213	3.526	0.872	1	5	248	3.350	0.922	1	5
Distribution	213	4.005	0.755	2	5	248	3.980	0.734	2	5
Workmanship	213	3.545	0.934	1	5	248	3.363	0.942	1	5
Production problems	213	3.925	0.785	2	5	248	3.810	0.800	1	5
Customer relation	213	3.535	1.168	1	5	248	3.282	1.106	1	5
Customer complaints	213	3.981	0.961	1	5	248	3.706	0.976	1	5
Industry dynamism	213	0.227	0.164	0.031	0.594	248	0.246	0.080	0.097	0.319
Firm size	213	184.056	259.594	17	2515	248	209.045	429.196	11	5445
Calibrated										
Incr. innovation performance	213	0.460	0.344	0.099	0.999	248	0.502	0.362	0.049	0.999
Human capital pool (large share of workers with:)										
University degree	213	0.471	0.289	0.169	0.999	248	0.464	0.340	0.099	0.999
PET degree	213	0.368	0.352	0.009	0.999	248	0.464	0.348	0.019	0.999
VET degree	213	0.383	0.375	0	0.999	248	0.459	0.371	0	0.999
HRM system										
Teamwork	213	0.742	0.439	0	1	248	0.839	0.369	0	1
Job rotation	213	0.296	0.457	0	1	248	0.246	0.432	0	1
Empowerment	213	0.284	0.140	0.049	0.779	248	0.332	0.161	0.059	0.849
High industry dynamism	213	0.763	0.347	0.009	0.999	248	0.699	0.244	0.429	0.999
Large firm	213	0.628	0.164	0.439	0.999	248	0.588	0.184	0.359	0.999

To measure environmental velocity, we draw upon the McCarthy et al. (2010) conceptualizations: The rate of change in demand is a standard measure for environmental velocity (Bourgeois & Eisenhardt, 1988; Smith, Smith, Olian, Sims, O'Bannon, & Scully, 1994) and is still in use (e.g., Nadkarni & Barr, 2008). We combine two items that measure the changes in demand in the main product market of the past and the future three years (measured on a 5-point Likert scale). We subtract the future demand change from the past one and calculate the absolute value from this difference. We purposely omit the direction of change, because the high values of our dynamism measure automatically result in changing conditions at the firm level (e.g., firms that are accustomed to a growing demand might more easily adapt to a further increase than to a decrease).

Table 3.1 shows the descriptive statistics for the sample we use for our analysis, a sample generated from a representative data set. As this data set contains missing values (predominantly in the HRM measures), we exclude all observations with at least one missing value in the variables relevant to our analysis. The resulting sample is thus no longer representative. Therefore, to compare the firms before and after the exclusion of missing values, we calculate the average firm size in the representative sample and use the survey weights in our calculation. Our final sample constitutes a selection of large firms.

3.3.2 Method and Calibration

fsQCA applies Boolean algebra for the calculation of causally complex configurations of the KC system (Ragin, 2008). Therefore, it requires a dataset that contains conditions ranging from 0 (non-membership) to 1 (full membership). We thus calibrate all conditions to sets. By performing the calibration, we assess the usefulness of a condition's variation. If, for example, firm size should be transferred into a set entitled "large firm" and the two largest firms have 2000 and 1500 employees, we can overlook this difference if we consider large all firms having 1000 or more employees. The direct method of calibration, as described by Ragin (2008), assesses a condition's variation by using three anchor points ("fully in," "crossover," and "fully out"). In our example, the two large firms would both receive a value of 1 if we specify 1000 as the "fully in" point. Similarly, all firms that have fewer employees than specified in the "fully in" point but more than specified in the "crossover" would receive a value that is smaller than 1 but larger than 0.5. A similar logic holds for the "fully out" point.[15] The next subsection discusses the calibration of our outcome and the explanatory conditions.

Each fsQCA configuration comprises core and peripheral conditions. Different Boolean minimization procedures determine these conditions. While core conditions result from the parsimonious solution, peripheral conditions result from the intermediate solution. To obtain the parsimonious solution, the Boolean minimization uses all logical remainders in the minimization process. For the intermediate solution, the researcher uses theoretical knowledge to specify associations between outcome and causal conditions. To determine the

[15] For a detailed description of the direct calibration method, see Ragin (2008).

intermediate solution, the Boolean minimization incorporates these previously specified associations.

3.3.2.1 Incremental innovation performance

For any evaluation of firms' innovation performance, the choice of a meaningful benchmark is crucial. We relate firms' sales percentage of highly improved products to the accompanying subsector-specific (high tech or traditional manufacturing) mean. Table A3.1 in the appendix shows the classification of the industries.

To be reliable, the benchmark value should represent the entire subsector, not merely a selective sample. Thus the calculation of the benchmark should be based on representative data. Before the exclusion of missing values, the data set is representative for the Swiss firm population in the manufacturing sector. To calculate the average innovation performance in each of the two subsectors, we use the raw data. As the innovation measure contains missing values, we cannot apply the given survey weights to obtain reliable values for the average subsector performance. Therefore, we calculate correction factors that reweight firms' sample weight according to the missing structure in the innovation measure. The correction factor that we calculate for every stratum is the number of firms that returned analyzable questionnaires divided by the number of firms that returned analyzable questionnaires with no missing values in the innovation measure.[16] A simple correction of all weights by the same factor is not feasible, because the distribution of the missing observations deviates from the stratification structure of the sample. After the correction of the survey weights, we apply the corrected survey weights to calculate the means per subsector.

Relating firms' performance to the sector or subsector level is a standard procedure only when QCA is applied to multi-sector data (Greckhamer, Misangyi, Elms, & Lacey, 2008). As in our study, Greckhamer et al. (2008) use multi-sector data. For the definition of the cut-off of their outcome (superior business-unit performance), they calculate the overall sample mean of business-unit performance and assign a 1 to all business units that have a higher return on assets than the sample mean and a 0 to those below that mean.

We use a similar procedure for the calibration of superior incremental innovation performance, i.e., we relate a firm's innovation performance to its peer group. This

[16] The underlying survey weight to which we apply our correction factors is calculated as follows: $w_{hi} = 1/(f_h*r_{hi})$, where f_h equals the ratio of the number of companies in stratum h in the sample and the number of companies in stratum h in the population and r_{hi} denotes the non-response probability of company i (Arvanitis, Hollenstein, Kubli, Sydow & Wörter, 2007).

benchmarking is necessary for the identification of configurations that allow firms to outperform their competitors. Greckhamer et al. (2008) use a very broad definition of a firm's peer group (i.e., all firms in the sample). We argue that narrowing the peer group to firms that share the same subsector gives the firm a better opportunity to observe and react to its peers. As the performance of those peers determines a firm's survival in the market, the performance of this subgroup might be a benchmark in which a firm is interested.

We therefore deviate from Greckhamer et al. (2008) by using the subsector means for calibration instead of the overall means. We subtract the subsector mean from the sales percentage of highly improved products for every firm in a subsector. As we focus on explaining superior incremental innovation performance, we set 0 as the value for the crossover (Greckhamer et al., 2008). This point reflects a performance that is precisely in line with the average subsector performance and is therefore neither superior nor inferior. We calculate, by subsector, standard deviations of the mean-corrected innovation performance measure. As the standard deviations vary substantially across subsectors, we select subsector-specific standard deviations as values for the "fully in" and "fully out" thresholds. We select a positive standard deviation for the "fully in" threshold and a negative one for the "fully out" threshold.

3.3.2.2 Explanatory conditions

We use four explanatory conditions that are crucial for a firm`s superior incremental innovation performance. The first set of conditions contains the educational composition of the workforce, thereby measuring a firm's human capital pool. The second set of conditions contains the use of HRM practices. The third condition measures firm size, the fourth industry dynamism.

Workforce composition measures and firm size

For the three workforce composition measures and firm size, we apply the same method we used for the calibration of the outcome: again we subtract the subsector means from the workforce composition measure and firm size, respectively. The 0 serves as the crossover. We use the standard deviation for the "fully in" and "fully out" points. A positive standard deviation constitutes the "fully in" point; a negative, the "fully out" point.

HRM measures

For the measurement of HRM practices we use teamwork, job rotation, and empowerment. As both teamwork and job rotation are binary conditions, we use them directly for our analysis.

Given that we focus on overall empowerment, not on particular areas, we combine 7 items—all measured on a 5-point Likert scale—to obtain the empowerment condition. Before combining the items into scales, we perform a principal factor analysis (Fiss, 2011). The results appear in Table 3.2. One factor has an eigenvalue greater than 1, indicating a one-factor solution for each subsector. We combine all items into one scale that shows a Cronbachs-alpha of 0.62 in traditional manufacturing and 0.70 in high tech manufacturing.

Table 3.2 Principal Factor Analysis for Responsibility Distribution

	Traditional manufacturing Factor 1	High tech manufacturing Factor 1
Survey item		
1. Work pace	0.234	0.423
2. Sequencing	0.475	0.540
3. Distribution	0.319	0.378
4. Workmanship	0.287	0.419
5. Production problems	0.361	0.470
6. Customer relation	0.669	0.724
7. Customer complaints	0.693	0.568
Eigenvalue	1.522	1.855

All items are measured on a scale ranging from 1 (worker is responsible) to 5 (supervisor is responsible).

The resulting scale pictures the distribution of decision-making responsibilities between workers and supervisor. While the value 1 indicates that the employee has all the decision-making responsibilities, the value 5 indicates that the supervisor has them all. Entitling the scale “empowerment,” we follow Fiss (2011) for the coding procedure of scales constructed from items measured on a 5-point Likert scale. Thus we set the “fully in” point at 1, the “fully out” point at 5, and the “crossover” point at 3.

Industry dynamism

To measure industry dynamism, we use the difference between the past and future demand developments in the market for a firm’s main product. To obtain a comparable measure across the two subsectors, we calculate the mean for each industry in every subsector and normalize the scale over the entire manufacturing sector. Thus a highly dynamic environment in high-tech manufacturing is comparable to a highly dynamic environment in traditional manufacturing.

3.3.3 Analysis

We follow Greckhamer et al. (2008) and run the analyses separately for each of the two subsectors. After the calibration of conditions into sets, the next step in fsQCA is the creation of a "truth table." For the selection of conditions associated with the outcome, we use consistency scores that can take values between 0 and 1. A consistency score of 1 means that the outcome displays the causal condition perfectly; a 0, not at all (Ragin, 2008). To obtain results with a meaningful consistency level, we code conditions as a condition that explains the outcome if its consistency score exceeds 0.84. To keep the fsQCA results from reflecting single cases, we set the minimum frequency cutoff at 3.

For the minimization procedure, we use the truth table algorithm implemented in the fsQCA software (Ragin, Drass, & Davey, 2006). This algorithm uses Boolean algebra to generate a more parsimonious solution from the underlying truth table. The most parsimonious solution contains only core conditions and uses all logical remainders for the minimization process. This solution is a superset of the intermediate solution. This intermediate solution uses only remainders chosen by the researcher according to his or her theoretical knowledge (Ragin, 2008). The intermediate solution thus contains the core conditions of the parsimonious solution and the peripheral conditions that are generated from theoretical knowledge.

3.4 Results

Table 3.3 shows the configuration of the fsQCA in both subsectors. For both solutions we obtain an overall consistency score of above the acceptance threshold of 0.8 (Fiss, 2011). The overall coverage for both solutions is 0.28, a value in line with studies using similarly sized data sets and frequency cutoffs (e.g., Fiss, 2011). We follow Ragin and Fiss (2008) in displaying the configurations, each of which is organized vertically. A condition included in a configuration can either be present (full circle) or absent (crossed circle). Empty spaces denote "don`t care" conditions, which can be either present or absent. Core conditions are displayed as large circles; peripheral conditions, as small circles.

3.4.1 Superior innovation performance

Configuration 1 in the traditional manufacturing sector contains the following two core elements: the presence of a concentration of university graduates and the absence of high industry dynamism.[17] The peripheral elements are the presence of large firm size and teamwork and the absence of job rotation and decentralization. These firms not only employ more university graduates (e.g., scientists or engineers) but are also larger than the average firm in the traditional manufacturing sector. Thus university graduates have relatively more opportunities for collaborations (teamwork) among one another or with the remaining workforce, with innovation possibly resulting not only from these collaborations but also from knowledge spillovers. The concentration of employees with university degrees increases the probability that the remaining workforce will interact with these higher educated employees. Thus the probability of knowledge spillovers also increases.

Configuration 2 consists of a concentration of workers with PET and VET degrees and the absence of large firm size. Peripheral conditions are the presence of teamwork and a highly dynamic environment and the absence of job rotation and decentralization. Due to the concentration of workers with PET degrees (e.g., master craftsmen or technicians) and VET degrees (journeymen), the firm facilitates knowledge exchange. The completion of a VET degree is a prerequisite for the majority of PET programs. Thus workers with PET degrees and workers with VET degrees have what Grant (1996a) calls "sophisticated common knowledge." Both use the same terminology and share a certain degree of knowledge. As they do not have to simplify ideas or problems when interacting, knowledge exchange among these workers is much easier. Thus the innovative potential in this configuration results from the collaboration of highly knowledgeable workers who can easily transfer their expertise to one another. This rapid knowledge exchange is especially valuable in the highly dynamic environment that these firms face.

Configuration 3 in the traditional manufacturing sector contains the following core conditions: the absence of a concentration of university graduates and the presence of job rotations and a concentration on workers with PET degrees. Peripheral conditions are the presence of large firm size, teamwork, and high industry dynamism, and the absence of empowerment. Due to the concentration on workers with PET degrees, more advanced practical knowledge is available in these firms than in the average firm in the sector. By applying teamwork and job

[17] All conditions that constitute the firm's human capital pool must be interpreted relative to the subsector average, e.g., the presence of a concentration of university graduates means that firms employ more university graduates than the subsector average.

rotation, firms belonging to configuration 3 implement an HRM system that leads to organizational learning and ensures the diffusion of advanced practical knowledge throughout the entire firm. Workers with PET degrees diffuse their knowledge either by directly participating in teamwork or job rotation, or by interacting with workers in different jobs or functions. Innovativeness therefore results from the combination of organizational learning and the availability of advanced practical knowledge.

Configurations 4-6 show KC systems in the high tech manufacturing sector. Configuration 4 contains the following core conditions: the presence of a concentration of university graduates, job rotation, and high industry dynamism and the absence of a concentration of workers with PET degrees. Peripheral conditions are the presence of teamwork and the absence of empowerment and large firm size. Configuration 4 is very similar to configuration 3, despite differences in the human capital pool. Configuration 4 combines teamwork and job rotation, thereby resulting in organizational learning. Instead of concentrating on workers with PET degrees, firms belonging to configuration 4 concentrate on university graduates. The mechanisms for configuration 4 remain similar to those described for configuration 3: Scientists and engineers exchange knowledge among one another more frequently, and given the application of teamwork and job rotation practices, the remaining workforce has a higher probability of interacting with one another. The relative importance of more theoretical knowledge, as opposed to practical knowledge, might occur because of the differences in knowledge requirements in the traditional and the high tech manufacturing sub sector.

Configuration 5 has the following core conditions: the presence of a concentration of workers with PET degrees and empowerment; the presence of a concentration of university graduates, teamwork, and high industry dynamism; and the absence of job rotation and large firm size as peripheral conditions. By concentrating on both university graduates and workers with PET degrees, these firms combine two types of expert knowledge: theoretical and advanced practical. As the high degree of empowerment helps engineers and master craftsmen to directly implement their ideas, one can reasonably assume that they jointly generate improvements of products and processes.

Table 3.3 Configurations explaining superior innovation performance in manufacturing

Sector	**Traditional manufacturing**			**High tech manufacturing**		
KC system	1	2	3	4	5	6
Human capital pool (large percentage of workers with:)						
University degree	●		⨂	●	•	
PET degree		●	●	⨂	●	●
VET degree		●				
HRM system						
Teamwork	•	•	•	•	•	⨂
Job rotation	⊗	⊗	●	●	⊗	⊗
Empowerment	⊗	⊗	⊗	⊗	●	⊗
High industry dynamism	⨂	•	•	●	•	⊗
Large firm	•	⨂	•	⊗	⊗	⊗
Consistency	0.76	0.81	0.90	0.84	0.83	0.78
Raw coverage	0.12	0.11	0.08	0.06	0.17	0.04
Unique coverage	0.09	0.08	0.08	0.06	0.17	0.04
Overall solution consistency	0.81			0.83		
Overall solution coverage	0.20			0.28		

Configuration 6 contains the following core conditions: the presence of a concentration of PET degrees and the absence of teamwork. Peripheral conditions are the absence of job rotation, empowerment, high industry dynamism, and a large firm size. Given the small firm size, formal HRM practices that induce knowledge sharing might not be necessary for innovation. Knowledge spillover from workers with PET degrees to the remaining workforce is one channel explaining the innovative potential of firms belonging to configuration 6. A different channel for innovation might be master craftsmen and technicians using their expert knowledge to generate innovations independently. Although this configuration contains less formal cooperation than configuration 1, both configurations share certain similarities, such as the concentration of a single skill and the low industry dynamism.

3.4.2 Quantifying the composition of firms' human capital pool

Table 3.3 shows KC system configurations that explain superior innovation performance. The information provided in this table is more detailed for the HRM system than for the human capital pool. The HRM system consists of two binary measures (teamwork and job rotation) and one set (empowerment) that we derive from a combination of items that are measured on a Likert scale. If, for example, we take configuration 5, that the HRM system combines the presence of teamwork, the absence of job rotation, and the presence of empowerment (i.e., giving workers more responsibilities than their supervisors) is intuitive. The interpretation of the results for human capital is less straightforward, because it depends on measures that are related to the means of the subsector.

To provide further information on the meaning of the presence or absence of, for example, a large percentage of university graduates, we calculate the means of all human capital conditions for those firms that are members (membership score ≥ 0.5) in the configurations shown in Table 3.3. Table 3.4 shows descriptive statistics for all firms that are members in one of the 6 configurations.

Table 3.4 Human capital pool composition in percentages (For firms with a membership score of at least 0.5 in one of the 6 KC systems).

	Traditional manufacturing			**High tech manufacturing**		
KC system	1	2	3	4	5	6
Human capital pool (Large percentage of workers with:)						
University degree	11.57		0.83	8.33	13.25	
PET degree		17.80	21.33	12.33	26.25	22.00
VET degree		59.60				
Observations	7	5	6	3	4	4

Note: Numbers for "don`t care" conditions are not reported in this table.

Table 3.4 shows that the composition of a human capital pool varies substantially between configurations. For example, a comparison between configuration 4 and 5 shows that the percentage of university graduates differs by 4 percentage points, although the condition "large percentage of workers with university degrees" is present in both configurations. These differences have strong implications for firms that aim at improving their innovation performance by adopting the configurations we have identified.

For example, let us assume a hypothetical firm in the high tech manufacturing sector that operates in a highly dynamic environment and has a low innovation performance. For simplicity we focus on workers with university degrees and workers with PET degrees. Assume that the firm applies no HRM practices and has the following workforce composition: workers with university degrees, 5 percent; workers with PET degrees, 10 percent; and the remaining workforce, 85 percent. We further assume that this firm chooses to adopt configuration 4. To improve its innovation performance, it could hire a small number of workers with university degrees and workers with PET degrees and introduce teamwork and job rotation. In this case the adoption of configuration 4 requires little changes in the human capital pool of the firm. We now assume that the hypothetical firm has the following workforce composition: workers with university degrees, 5 percent; workers with PET degrees, 20 percent; and the remaining workforce, 75 percent. With this workforce composition, the firm might not only hire but also lay off workers to adopt configuration 4.

The increased fluctuation that results from reshaping firms' human capital pool might generate further obstacles to the introduction of HRM practices (e.g., introducing teamwork before reshaping the composition of human capital might hamper teamwork effectiveness, because this reshaping might affect team compositions and collaborations). The adoption of configuration 4 in the latter case might therefore be much more demanding than in the former.

The results in Table 3.4 and our example both show that firms might select configurations according to their proximity to a configuration. We also show that firms that have less in common with a configuration might face several obstacles during the adoption process. The correct sequencing of single adoption steps in particular is crucial for a successful adoption.

3.4.3 Building a taxonomy

After identifying configurations that explain superior innovation performance and explaining their internal mechanisms, we categorize these configurations by using theories and typologies of innovation and HRM. For this categorization, we summarize and label the human capital pool and the HRM system of the configurations in Table 3.3. From this categorization, we compare our configurations with the Burns and Stalker (1961) typology, a generic typology that not only contains strong implications for KC and innovation but also takes firms' environment into account.

In their typology Burns and Stalker (1961) define two forms of a management system: the mechanistic and the organic form. These two forms are the extreme poles of a continuum of management systems. The mechanistic form characterizes firms operating in a stable environment. These firms have strong hierarchical structures that foster interactions between supervisors and subordinates, with knowledge concentrated at the top of the hierarchy. Each task is differentiated into single sub-tasks that require narrow and specific knowledge. In contrast, the organic form characterizes firms operating in a dynamic environment. These firms have a network structure that allows communication between employees with different functions and ranks. Moreover, as organic firms engage in joint problem solving, they therefore combine the special knowledge of their employees. This knowledge can be located anywhere in the network structure of the firm.

Table 3.5 summarizes the results in Table 3.3 in a taxonomy that contains four types. The first type, "single-skill concentration," comprises configurations 1 and 6 in Table 3.3. Both share low industry dynamism and a similar human capital pool that sets the focus on a single skill. The HRM systems of these two configurations contain neither job rotation nor empowerment, and only the HRM system of configuration 1 contains teamwork. As firms in configuration 1 are large, the application of teamwork might be a necessary condition for overcoming potential "ossifying tendencies of large organizations" (Brown and Duguid, 1991) that might otherwise hamper innovation. Taken together, the HRM systems of configuration 1 and 6 are more control-based than commitment-based systems (Arthur, 1992, 1994; Walton, 1985). We thus categorize the single-skill concentration type as a "mechanistic" form according to the Burns and Stalker (1961) typology.

We continue by looking at the other pole of the Burns and Stalker (1961) typology, the "organic" form. The "empowerment" type is consistent with this organizational form. This type fits configuration 5 which contains highly diversified human capital and an HRM system that contains both, teamwork and empowerment. Arthur (1992, 1994) and Walton (1985) argue that the empowerment of the workforce and socializing activities induced by the application of teamwork are parts of a commitment system. We follow Walton (1985) by calling the HRM part of the KC system "commitment based." By relating configuration 5 to the organic form of the Burns and Stalker (1961) typology, we find substantial overlap. The organic form is appropriate for firms facing changing conditions. Consistent with this prediction, we find the presence of high industry dynamism in our empowerment type.

The organic form also consists of a management system that induces commitment by shaping a collaborative environment and that gives authority to workers with expert knowledge on a particular task. In our empowerment type we find these features in the application of teamwork and the empowerment of the workforce. Although the organic form does not directly deal with knowledge in terms of levels, it nevertheless covers the importance of expert knowledge and its diffusion within the firm. Firms that belong to the empowerment type consistently focus on more expert knowledge and a stronger knowledge diversification than their competitors.

Table 3.5 Taxonomy derived from configurations

		Types			
		Empowerment	**Vocational skill mix**	**Organizational learning**	**Skill concentration**
Classifcation categories	**Human capital pool**	Diversified	Diversified	Single skill concentration	Single skill concentration
	HRM system	Commitment	Control	Commitment	Control
	Industry dynamism	High	High	High	Low
	Typology (Burns and Stalker 1961)	Organic	Hybrid	Hybrid	Mechanistic

Two types lie in between the two poles of the mechanistic and organic forms. The “vocational skill mix” type, based on configuration 2 in Table 3.3, combines highly diversified human capital with a control-based HRM system. Through the concentration of workers with different vocational education degrees, firms in configuration 2 use the shared knowledge base of workers with PET and VET degrees. This shared knowledge base has two functions that contribute to innovation: First, it serves as a common ground that enables communication between these workers without losing specialized knowledge (Grant, 1996a). Second, in combination with workers’ high potential for self-organizing, it enables multi-actor collaborations (Fjeldstad, Snow, Miles, & Lettl, 2012). Consistent with the model proposed by Fjeldstad et al. (2012), the HRM system in configuration 2 contains hierarchical elements such as the absence of empowerment.

The fourth type, “organizational learning,” derives from configurations 3 and 4. It combines human capital concentrated on a single skill and an HRM system focused on organizational learning. The innovative potential of this type stems from the joint application of teamwork and job rotation. These practices allow knowledge sharing within and across groups, thereby enabling organizational learning (Brown & Duguid, 1991; Collins & Smith, 2006; Smith et al., 2005). We label this HRM system “commitment-based” in line with Arthur (1992, 1994) and Walton (1985). This system facilitates the diffusion of knowledge from a firm’s human capital pool.

3.5 Discussion

This chapter analyzes superior incremental innovation performance by integrating a firm’s human capital pool and HRM system in a knowledge creation (KC) system. We follow Kogut and Zander (1992) in arguing that knowledge recombinations constitute a source of innovation. To achieve these knowledge recombinations, firms require a knowledge stock that contains innovation-relevant knowledge and interacting workers who induce a knowledge flow within and between levels. Following Wright et al. (2001), we argue that complementarities within and between both firms’ human capital pool (knowledge stock) and HRM system (workers’ behavior that induces knowledge flow) exist. We show that these complementarities influence knowledge exchange between workers and we reformulate the Wright et al. (2001) model to a KC system.

Our review of the empirical HR and innovation literature reveals a gap between theoretical models and their empirical implementation. Although several HR theories and typologies argue for integrating human capital and HRM and apply configurational theory to their models, empirical research only partially considers them. The majority of empirical studies investigating innovation take either the HRM or human capital perspective. Studies taking the HRM perspective argue that either single practices or an HRM system influences innovation, whereas studies taking the human capital perspective focus on average human capital or diversity in human capital. While a few studies combine both perspectives, the empirical approaches in which these studies are rooted in use universalistic or contingency theory, thereby neglecting configurational theory.

Our study closes this gap by examining KC system configurations that explain superior incremental innovation performance. For our analysis we apply fsQCA, a method that allows us to recognize important properties of configurational theory, such as equifinality and causal complexity. Our empirical analyses are based on a large data set on Swiss manufacturing firms.

Our results show that firms can achieve superior incremental innovation performance through multiple pathways. These pathways highly depend on the environmental dynamism in a firm's industry. Our analysis of two subsectors (high tech and traditional manufacturing) shows similarities in the structure of pathways between the two. Consequently, we use our results to build a taxonomy that we relate to HR and innovation theory. To classify our results, we use Burns and Stalkers' (1961) generic typology on management systems and Arthurs' (1992, 1994) classification of HR systems.

The types that we identify cover the entire range of the Burns and Stalker (1961) typology. We aggregate two configurations that share a low dynamic environment, concentration of a single skill, and disregard of HRM practices to a taxonomy that we call "single skill concentration." This type highly correlates with and overlaps the mechanistic form of management proposed by Burns and Stalker (1961). We also find a type that represents Burns and Stalkers' (1961) organic form. This type is characterized by concentration on diverse skills, a high skills level, and an empowerment-based HRM system. We call this type "empowerment."

We identify two additional types that lie between the mechanistic and organic forms (Burns & Stalker, 1961). Both types share high industry dynamism but differ strongly in their composition. One type, which we call "vocational skill mix," contains a strong focus on diversified vocational skills but has a very limited application of HRM practices. The other type, which we call "organizational learning," concentrates on single skills and consists of an HRM system with a strong orientation towards organizational learning.

Our findings have both theoretical and practical implications. By showing that superior innovation performance has multiple pathways, we provide a starting point for the development of typologies based on the mechanisms of knowledge exchange. These typologies could describe complementary and substitutive relationships within and between a human capital pool and an HRM system. We also identify four types consistent with Burns and Stalkers' (1961) typology. Two types have a high overlap with their original mechanistic and organic forms, respectively. The other two types are hybrids, located between the two poles. As our analyses do not allow us to draw conclusions on the dynamics of management forms, the hybrid forms we identify could either constitute fixed systems or reflect transitory stages of pathways that firms use to reach one of the two poles.

The finding of multiple pathways toward superior innovation performance is also valuable from a practical perspective. Our results suggest that, for firms to outperform their peer group, they require knowledge about that peer group. When employing workers from different educational backgrounds, firms must have in-depth knowledge on educational complementarities. Formalizing interactions when educational differences appear insurmountable might not generate benefits that outweigh the costs that maintaining such work organization causes. Instead, firms might consider trading off the employment of workers who share a common ground against the application of HRM practices.

Considering, the finding of this chapter, that complementarities within and between a firms human capital pool and HRM system explain multiple pathways toward superior innovation performance, we focus in the next chapter on the analysis of complementarities within a firms' human capital pool.

Appendix

Table A3.1 Industry and sector classification

Industry number	Industry title	Sector
Manufacturing		
1	Manufacture of food products, beverages and tobacco	Traditional manufacturing
2	Manufacture of textiles and textile products	Traditional manufacturing
3	Manufacture of wearing apparel; dressing and dyeing of fur and Manufacture of leather and leather products	Traditional manufacturing
4	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plainting materials	Traditional manufacturing
5	Manufacture of pulp, paper and paper products	Traditional manufacturing
6	Publishing, printing and reproduction of recorded media	Traditional manufacturing
7	Manufacture of coke, refined petroleum products and nuclear fuel and manufacture of chemicals and chemical products	High tech manufacturing
8	Manufacture of rubber and plastic products	High tech manufacturing
9	Manufacture of other non-metallic mineral products	Traditional manufacturing
10	Manufacture of basic metals	Traditional manufacturing
11	Manufacture of fabricated metal products, except machinery and equipment	Traditional manufacturing
12	Manufacture of machinery and equipment n.e.c.	High tech manufacturing
13	Manufacture of electrical machinery and apparatus n.e.c.	High tech manufacturing
14	Manufacture of office machinery, data prcessing devices, Manufacture of radio, television and communication equipment and apparatus, manufacture of medical and srugcal equipment and orthopaedic appliances, manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, manufacture of industrial process control equipment and manufacture of optical instruments and photographic equipment	High tech manufacturing
15	Manufacture of watches and clocks	Traditional manufacturing
16	Manufacture of transport equipment	High tech manufacturing
17	Manufacture of furniture, jewellery, musical instruments, sports goods, games and toys and other goods, recycling	Traditional manufacturing
18	Electricity, gas and water supply	Traditional manufacturing
Construction		
19	Construction	Construction
Services		
20	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel and wholesale trade and commission trade, except of motor vehicles and motorcycles	Traditional services
21	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods	Traditional services
22	Hotels and restaurants	Traditional services
23	Land transport; transport via pipelines, Water transport, air transport and supporting transport activities; activities of travel agencies	Traditional services
24	Financial intermediation; insurance (excluding compulsory social security)	Modern services
25	Real estate activities and Renting of machinery and equipment without operator and of personal and household goods	Traditional services
26	Computer and related activities and research and development	Modern services
27	Other business activities	Modern services
28	Other service activities	Traditional services
29	Post and telecommunications	Modern services

Source of industry titles: Swiss Federal Statistical Office (2002)

Chapter 4 Educational Spillovers at the Firm Level: Who Benefits from Whom?

(A (former) version is also available as: "Educational Spillovers at the Firm Level: Who Benefits from Whom?" Swiss Leading House Working Paper no. 65 (2011). By Uschi Backes-Gellner, Christian Rupietta and Simone Tuor Sartore.)

4.1 Introduction

Educational or human capital spillover effects have been of increasing interest to economists over the past three decades. Studies focus on educational spillover effects at different aggregation levels such as region (e.g. Ciccone & Peri, 2006; Moretti, 2004a; Rauch, 1993), industry (e.g. Kirby & Riley, 2008; Sakellariou & Maysami, 2004), and firms or workers (e.g. Barth, 2002; Battu, Belfield, & Sloane, 2003; Bratti & Leombruni, 2009). The common underlying assumption in research on spillover effects is that spillovers arise either from the individuals with the highest education level (e.g. Moretti, 2004b) to the individuals with lower levels of education or from the average education level measured in number of years (e.g. Rauch, 1993). This assumption neglects that educational spillovers can also arise from having different types of knowledge even if the level or the length of education is the same.

If individuals are heterogeneous in terms of the type of their education, we expect that this will also cause educational spillovers due to complementary heterogeneous knowledge. In such cases, the mere distinction by educational level would not cover all relevant educational dimensions. Especially in countries that have a Vocational Education and Training (VET) system that offers high quality training at the secondary level, such as Austria, Germany, Switzerland, or Denmark, a mere distinction by educational level might prove insufficient.[18] Therefore analyzing educational spillover effects, not only by the level but also by the type of education is important to catch the whole range of possible spillovers.

This paper contributes to the spillover literature in two ways. First, we develop a model of reverse spillovers that establishes informational spillovers as the underlying concept of educational spillovers. Following Jovanovic and Robs' (1989) model on informational spillover, we integrate educational type as an additional dimension in the spillover literature. By applying the informational spillover model, we also include predictions on the functional form in our hypotheses. In line with Battu et al. (2003) we expect a non-linear relationship.

[18] Secondary vocational education in Austria, Germany, and Switzerland primarily consists of a combination of extensive workplace training and vocational schooling. The training programs typically last 3-4 years and convey general and occupation-specific skills.

They find a positive but diminishing return from an increase in the overall educational level of a workplace. Second, we empirically analyze the spillovers to tertiary education from the presence of co-workers with secondary vocational education (i.e. dual-track VET).

To test our hypotheses, we use data from the Swiss Earnings Structure Survey (ESS), a large panel of employer-employee data, and estimate Mincerian earnings equations (Mincer, 1974).[19] The ESS is a perfect match for our empirical analysis, as the data set contains information on workers' education and wages and allows us to measure education by using educational degrees instead of years of schooling. In our estimation strategy we consider the potential endogeneity of a firm's workforce composition and use an instrument for the number of workers with VET degrees. Since the tradition of training apprentices is more widespread in the German-speaking regions of Switzerland than in the non-German-speaking regions, we use a firm's location as an instrument for the employment of workers with VET degrees.

Our results show that the effect from an increase in the number of workers with VET degrees on the productivity of workers with tertiary education is positive but diminishing. The effect is robust against the inclusion of regional, year, and sector controls, as well as firm controls. Furthermore, the results remain robust with fixed effects estimation.

The remainder of the paper is structured as follows. Section 2 presents the theoretical considerations and derives our hypotheses. Section 3 explains our estimation strategy, and Section 4 introduces the data set. Section 5 presents our empirical results and robustness checks. Section 6 concludes.

4.2 Theory

From a traditional spillover perspective highly skilled or educated workers generate positive spillover effects to lower educated workers (Ciccone & Peri, 2006; Moretti, 2004a, 2004b). This perspective neglects that education differs not only by level but also by type and that spillovers could thus go from any type of education to another type of education, including reverse spillovers from workers with lower degrees to workers with higher degrees. This is in line with the argumentation of Jovanovic and Rob (1989). In their model on informational spillover effects, they argue that any difference in knowledge between two workers can cause a spillover effect if these workers interact. They argue that the exchange of different ideas between workers leads to an improvement of ideas or to imitation of the more valuable ideas,

[19] This procedure is based on Martins and Jin (2010).

depending on the degree of differences in knowledge of the interacting workers. In their model knowledge differences are kept simple: they stem from differences in the level of education. Higher levels are assumed to have more knowledge and thus spillover effects are oneway effects and go from higher levels of workers to lower levels of workers. We built on Jovanovic and Rob's basic ideas and extend them by arguing that differences in knowledge might also result from differences in educational types and that spillover effects can thus also flow from VET workers to academic workers, which we call reverse spillovers.

To derive the hypotheses for our empirical analyses, we follow Moretti (2004a, 2004b), who models city-level productivity using a Cobb-Douglas technology and specifies two types of labor.[20] We model the productivity of tertiary-educated workers depending on the educational composition of a firm's workforce, i.e. the number of workers with a different knowledge set generated by VET degrees. We start with the model of Moretti but omit physical capital in the production function for simplicity (because the implications from the model remain unchanged and because our main interest lies in the composition of the workforce). Unlike Moretti, we use two types of workers T and S and model firm-level productivity as follows:

$$Q = AT^{\alpha}S^{\beta} \tag{4.1}$$

where A is a productivity shifter, and T and S denote the number of workers with a tertiary education and the number of workers with a secondary vocational education (VET degree), respectively. We assume that firms have a linear labor cost function. For the minimization of labor costs (or equivalently the maximization of output), we calculate the partial derivatives $\frac{\delta L}{\delta T}$ and $\frac{\delta L}{\delta S}$ of:

$$L = W_T T + W_S S + \lambda(Q - AT^{\alpha}S^{\beta}) \tag{4.2}$$

The first order conditions are given by:

$$\frac{\delta L}{\delta T} = W_T - \lambda\alpha AT^{\alpha-1}S^{\beta} = 0 \tag{4.3}$$

$$\frac{\delta L}{\delta S} = W_S - \lambda\beta AT^{\alpha}S^{\beta-1} = 0 \tag{4.4}$$

Solving (4.3) and (4.4) for λ and substituting (4.4) into (4.3) leads to the marginal rate of substitution of tertiary-educated workers and workers with VET degrees:

[20] As we use aggregated firm-level measures, we exclude individual human capital from our model.

$$\frac{W_T}{W_S} = \frac{\alpha S}{\beta T} \tag{4.5}$$

Thus, an increase in the number of workers with VET degrees is associated with an increase in the productivity of tertiary-educated workers and thus an increase in output. With an increase in the number of workers with VET degrees, productivity of tertiary-educated workers rise.

In line with the derived marginal rate of substitution and the model on informational spillovers—spillover effects occur if the type of education, and thus the ideas that the workers possess, differs. As tertiary educated-workers and workers with VET degrees differ in their level and type of education. We derive our first hypothesis:

H1: An increase in the number of workers with VET degrees has a positive effect on the productivity of workers with tertiary education.

As an increase in the number of co-workers with a given education might have a different impact depending on the initial number of these co-workers, we expect a nonlinear effect of educational spillovers. We model this effect in analogy to nonlinear forms of individual returns to education (Card, 1999). We argue that the return to an increase in the number of workers with VET degrees is positive but diminishing. An initial increase in the percentage of workers with VET degrees has a stronger impact than an additional increase.

H2: The positive effect from workers with VET degrees on the productivity of workers with tertiary education diminishes with the number of workers with VET degrees.

4.3 Data and descriptive statistics

For our empirical analysis, we use the Swiss Earning Structure Survey (ESS), a representative data set conducted biennially by the Swiss Federal Statistical Office. This data set is well suited for our analysis because it contains information on individual characteristics (e.g. wages, education, and tenure) and firm-level attributes (e.g. firm size, sector, and region). To generate a firm panel that allows us to control for time and firm-specific fixed effects, we aggregate the data to the firm level. We use data from 1998 through 2004.

Before aggregating the data, we restrict our sample in the following way. First, we restrict it to companies in the private sector.[21] For the calculation of the firm-average wages of workers

[21] The aggregation of the data results from the estimation strategy we choose in the following section.

with a tertiary education, we focus on workers aged 25 to 60.[22] Given the estimation of a fixed time and a firm-specific effect, all firms observed only once during the observation period, as well as firms switching to another sector, are excluded. Because we are interested in how the wages of tertiary-educated workers are affected by workers with VET degrees types of education, we restrict our data set to firms employing at least five workers and at least one worker with a tertiary education. After these restrictions, we aggregate our data set to the firm level. Table 4.1 shows the descriptive statistics.

Table 4.1 Descriptive statistics (firm level)

Variable	Obs	Mean	Std. Dev.	Min	Max
Log average gross monthly wages	22,846	8.799	0.236	8.019	9.829
Log average gross monthly wages of tert. educ.	22,846	9.054	0.275	7.956	9.929
Number of tertiary-educated workers	22,846	14.07	72.17	1	2,679
Number of workers with VET degrees	22,846	30.09	128.1	0	6,388
Number of workers with other education	22,846	18.09	111.5	0	5,667
Firm size	22,846	62.25	262.5	5	9,973
Male	22,846	0.600	0.259	0	1
Tenure	22,846	8.197	4.034	0	34.80
Age	22,846	41.00	4.733	22.27	63.20
Part-time	22,846	0.257	0.264	0	1

Source: Swiss Earning Structure Survey 1998-2004; authors' calculations

To investigate the relationship between the productivity of tertiary-educated workers and the educational composition of the workforce, we use monthly gross wages as a measure for measuring productivity assuming that wages reflect productivity sufficiently well. Wages in the ESS contain, in addition to time-based components, also performance-based components such as: bonus pay, commissions, and piece rates. Thus we are confident to use wages as a proxy for workers' productivity.

Our dependent variable is the log of average monthly gross wages of workers with tertiary education. We use real wages (2005 = 100) for our analysis. The ESS contains information on the highest educational degree of each worker, which we categorize in three categories: firstly, tertiary education, including workers who are graduates of one of the federal institutes

[22] In Switzerland, workers younger than 25 are unlikely to be university graduates, whereas workers older than 60 have the possibility of retiring up to two years before reaching the official retirement age of 65 for males and 64 for females. Workers older than 60 are assumed to be a heterogeneous group, as some stop working before reaching retirement age or continue working after it (Die Bundesversammlung der Schweizerischen Eidgenossenschaft 2012). Therefore, we use only the wages of workers aged 25 to 60. To calculate the educational composition of the workforce, we release the prior restriction to obtain a more precise number for the working environment of the workers in our sample.

of technology, a university, a university of applied science,[23] a pedagogical university, or a higher vocational school, secondly VET education including workers who have completed dual-track VET, thirdly other education including workers who have completed only high school or lower, or with a not classifiable foreign education.

Additionally, we include several control variables aggregated at the firm level. We aggregate for each firm and year the following individual variables at the firm level: being male (dummy), age and age squared (in years), tenure and tenure squared (in years), and working part time (dummy). At this level, we also include sector, region, and year (all categorical).

4.4 Estimation strategy

We follow earlier work by Martins and Jin (2010) and aggregate a Mincerian earnings equation on the firm level, because we are interested in spillover effects on the firm level. Because of the aggregation of the data at the firm level, we can include firm fixed effects that control strategic human resource management decisions affecting the education and ability distribution of the workforce. In addition, a Mincerian earnings equation allows the inclusion of the squared number of workers with VET degrees in our analysis, so that we can test for a nonlinear relationship. Doing so would not be possible if we derived our estimation equation directly from the Cobb-Douglas production function that we presented in the theory section.

In our first specification, shown in equation (4.6), we use the logarithm of average wages of tertiary-educated workers as a dependent variable. After sorting workers into three categories (tertiary education, VET, and other education), we calculate the number of workers belonging to each category for each firm. We use these three variables as our explanatory variables. The main explanatory variable in our equation is the number of workers with VET degrees. To test for a nonlinear relationship, we calculate the squared number of workers in each category.

$$y_{jt} = \sum_{k=1}^{3} \beta_k e_{kjt} + \sum_{k=1}^{3} \gamma_k e_{kjt}^2 + X_{jt}\delta + \varepsilon_{jt} \tag{4.6}$$

We further add controls, denoted X_{jt}, for average firm-specific characteristics, such as average age, average tenure (and their squares), the percentage of male workers, and the percentage of part-time workers. Furthermore, we add controls for region, sector, and year. Our first specification does not take into account factors that are time-invariant and potentially correlated with the educational composition of the firm, such as the average ability of the

[23] A university of applied science offers 3-year bachelors and 2-year masters programs containing more practical education, in comparison to universities or federal institutes of technology, which offer more theoretical education.

workforce. If these fixed factors affect the wages of tertiary-educated workers, equation (4.6) would be inconsistent. The panel structure of our data set allows us to include firm fixed effects to overcome this problem. The inclusion of firm fixed effects controls for factors such as high wage level, high tech firm, and a broad firm size class. Equation (4.7) shows our second specification, which includes firm fixed effects:

$$y_{jt} = \alpha_j + \sum_{k=1}^{3} \beta_k e_{kjt} + \sum_{k=1}^{3} \gamma_k e_{kjt}^2 + X_{jt}\delta + \varepsilon_{jt} \qquad (4.7)$$

To overcome potential endogeneity problems, we use an instrument for the number of workers with VET degrees. Since the tradition of training apprentices is more widespread in the German-speaking regions of Switzerland than in the non-German-speaking regions,[24] a firm located in a German-speaking region is more likely to employ workers with VET degrees and region can be used as an instrument.

For the IV estimation, we use a dummy variable that indicates whether the majority of the population of a region speaks German. We define a region as German-speaking if at least 50% of the population speaks German. For this classification, we use data from the 2000 Swiss Federal Population Census. We include the dummy variable in the first stage to obtain predictions for the number of workers with VET degrees, which we can include in the second stage. To avoid specification error, we use a linear specification for our IV estimation. Regardless of the functional form, linear IV estimates contain an average effect analogous to the local average treatment effect (LATE) (Angrist & Krueger, 2001).

Furthermore, the use of firm-level data requires a correction of the standard errors for clustering at the firm level. Therefore, we use cluster-robust standard errors (Moulton, 1990) in our estimations

[24] The categorization of being German-speaking is unambiguously possible for six of the seven major regions in Switzerland. One major region, Espace Mittelland, has a high linguistic heterogeneity (three French-speaking and two German-speaking cantons). For this major region, we use cantonal data to calculate our instrument. As our sample has no information on the location of firms in 2002 and 2004 at the cantonal level, we use observations from 1994 and the panel structure of our data set to categorize firms in 2002 and 2004. This procedure is reliable because of the low mobility of firms in Switzerland. (For example, Bodenmann & Axhausen, 2012, show that in the St. Gallen region, 1.77% of the companies within a period of 15 years starting in 1991 relocated; furthermore, most of the relocations occurred within the St. Gallen region.) Given this categorization and data on the linguistic distribution for each canton (2000 Swiss Federal Population Census), we calculate a dummy variable indicating German-speaking and non-German-speaking regions.

4.5 Results

4.5.1 Ordinary least squares (OLS) estimates

Table 4.2 provides the OLS estimates for testing our hypotheses. According to hypothesis 1 (H1), we expect a positive effect from an increase in the number of workers with VET degrees on the productivity of workers with tertiary education. Moreover, according to hypothesis 2 (H2), we expect that the return to an increase in the number of workers with VET degrees is positive but diminishing. As the results for the number of workers with VET degrees are robust throughout the different specifications, we focus on specification 5, which includes the full set of control variables (Table 4.2).

Table 4.2 Non-Linear Spillover Effects of Workers with VET on Workers with Tertiary Education (OLS Estimation)

OLS Regressions	Spec. (1)	Spec. (2)	Spec. (3)	Spec. (4)	Spec. (5)
Dep. Var.: Log average gross monthly wages of tert. educ.					
Number of workers with:					
Tertiary Education	0.02614***	0.03226***	0.02931***	0.00534	0.00518
	(3.47)	(4.29)	(4.19)	(0.80)	(0.78)
VET	0.02748***	0.02176***	0.01233***	0.01179***	0.01179***
	(5.85)	(4.93)	(3.05)	(2.83)	(2.83)
Other	-0.02104***	-0.02210***	-0.01774***	-0.00122	-0.00121
	(-4.04)	(-3.85)	(-3.33)	(-0.29)	(-0.29)
Sq. number of workers with:					
Tertiary Education	-0.00128***	-0.00152***	-0.00134***	-0.00041	-0.00040
	(-4.35)	(-5.15)	(-4.96)	(-1.43)	(-1.41)
VET	-0.00051***	-0.00039***	-0.00022**	-0.00028***	-0.00028***
	(-3.39)	(-3.16)	(-2.51)	(-3.13)	(-3.13)
Other	0.00035**	0.00043**	0.00037**	-0.00004	-0.00004
	(2.26)	(2.28)	(2.17)	(-0.41)	(-0.41)
Controls:					
Firm characteristics	no	yes	yes	yes	yes
Regional controls	no	no	yes	yes	yes
Sector controls	no	no	no	yes	yes
Year controls	no	no	no	no	yes
R-squared	0.01	0.06	0.10	0.19	0.19
N	22,846	22,846	22,846	22,846	22,846

Note: Cluster-robust t-statistics in parentheses (Cluster level: Firm). Number of workers was divided by 100.
* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

The coefficient for the number of workers with VET degrees is positive and statistically significant at the 1% level. Using the coefficients from specification 5 for the squared coefficient we calculate that the maximum effect is reached at 2105 workers with VET degrees. This indicates that for the average firm (i.e. 30 workers with VET degrees) an increase in the number of VET workers results in a higher productivity of workers with tertiary education. This result changes only for very large firms, i.e. only for firms exceeding the maximum of 2105 VET workers additional VET workers will have no longer positive effects on tertiary educated workers. Thus, for the majority of firms, we find support for both hypotheses: Tertiary-educated workers benefit from interacting with workers with VET degrees (H1), and the returns diminish as the number of workers with VET degrees increases (H2).

In contrast to workers with VET degrees, the number of workers with other qualifications is negatively associated with the productivity of tertiary-educated workers. This result is in line with Jovanovic and Robs' (1989) model: During an interaction, workers' knowledge can never be reduced but may only be increased as a result of additional information. In this case, we expect that the knowledge set of workers with other qualifications is largely a part of the knowledge set that tertiary-educated workers have. Those parts that do not overlap might not have any influence on the productivity of tertiary-educated workers.

Although we include a full set of control variables in specification (5) in Table 4.2, our results could be biased as a result of omitted time-invariant variables correlated with both average wages of tertiary-educated workers and the educational composition of a firm. In the next section, to capture unobserved time-invariant variables at the firm level, we include a firm-level fixed effect in our equations.

4.5.2 OLS estimates with firm-fixed effects

Table 4.3 shows the estimation results of equation (4.7). In the first column, we include no control variables at the firm level. We focus on specification 4, because the results are robust against the inclusion of the full set of control variables. The results confirm the results of Table 4.2: positive but diminishing spillover effects from VET workers to tertiary educated workers.

We again calculate the number of workers with VET degrees where the effect is maximized from specification 4. The maximum is at 3948 workers with VET degrees. This again shows that for the majority of firms, tertiary-educated workers benefit from interacting with workers with VET training (H1) and that these returns diminish with the number of workers with VET degrees employed (H2).[25]

These results support the robustness of the previous specifications against time-invariant factors, which are potentially correlated with firm-specific educational composition and tertiary-educated workers' productivity. As we expected from the theory on informational spillovers, workers with tertiary education benefit from interacting with workers with VET degrees.

Table 4.3 Non-Linear Spillover Effects of Workers with VET on Workers with Tertiary Education (Fixed-Effects Estimation)

FE Model	Spec. (1)	Spec. (2)	Spec. (3)	Spec. (4)
Dep. Var.: Log average gross monthly wages of tert. educ.				
Number of workers with:				
Tertiary Education	-0.05477***	-0.05623***	-0.05633***	-0.05726***
	(-6.63)	(-6.70)	(-6.69)	(-6.72)
VET	0.02244***	0.02254***	0.02245***	0.02211***
	(4.66)	(4.66)	(4.67)	(4.59)
Other	0.00111	0.00154	0.00135	0.00133
	(0.24)	(0.33)	(0.29)	(0.29)
Sq. number of workers with:				
Tertiary Education	0.00173***	0.00180***	0.00180***	0.00184***
	(4.54)	(4.46)	(4.43)	(4.49)
VET	-0.00028***	-0.00029***	-0.00028***	-0.00028***
	(-3.60)	(-3.59)	(-3.54)	(-3.50)
Other	0.00007	0.00007	0.00008	0.00008
	(0.87)	(0.88)	(0.91)	(0.93)
Controls:				
Firm characteristics	no	yes	yes	yes
Regional controls	no	no	yes	yes
Year controls	no	no	no	yes
R-squared	0.00	0.02	0.02	0.02
N	22,846	22,846	22,846	22,846

Note: Cluster robust t-statistics in parentheses (Cluster level: Firm). Number of workers was divided by 100.
* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Comparing the results of the OLS regressions (Table 4.2) with the results of the FE estimations (Table 4.3), we find that while the results for the number of workers with VET degrees remains stable, the results for the number of workers with tertiary education are

[25] The calculated turning points should not be interpreted as constituting a target value that firms should achieve. Instead, they show that the productivity of workers with tertiary education improves due to an increase in the number of workers with VET degrees.

different. We find a positive but diminishing return of the number of workers with tertiary education on their average productivity when using OLS regressions and a negative but increasing return when using FE estimations. This change in the functional form can be explained by the inclusion of sector dummies and fixed effects, respectively. While the diversity of qualifications within tertiary education might differ across sectors and firms, tertiary-educated workers learn from other tertiary-educated workers if this diversity is high (i.e. many different qualifications at the tertiary level in a single sector exist). After the inclusion of sector dummies, a change in the statistical significance of the coefficients causing the reversed functional form occurs. While the coefficients remain positive, the significance level indicates that they are not different from zero.

The fixed effects estimator controls for factors such as high average wage level, use of high technology, and broad firm-size classes. These effects do not influence the estimates we report in Table 4.3.

4.5.3 Robustness check: Instrumental variable estimates

As a robustness check, we conduct an instrumental variable estimation. Unobservable variables correlated with both the average wage of tertiary educated workers and the number of workers with VET degrees within a firm might bias the OLS and fixed effects estimations. We use a dummy indicating a German-speaking region as defined in the estimation strategy section as the instrument for the number of workers with VET degrees. Firms in German-speaking regions are more likely to train apprentices and to employ workers with VET degrees.

Table 4.4 shows the mean value comparison between firms located in German-speaking regions and non-German-speaking regions. As expected, the percentage of workers with VET degrees is higher in firms in German-speaking regions than in firms in non-German-speaking regions. These findings are in line with official statistics by the Federal Office for Professional Education and Technology (OPET) on the provision of dual-track VET: Firms in German-speaking regions offer more dual-track VET than firms in non-German-speaking regions (OPET 2010).

Table 4.4 Mean value comparison by linguistic region

Variable	Mean		p-value
	German-speaking region	Non-German-speaking region	(Difference equal to 0)
Log average gross monthly wages	8.8101	8.7789	0.0000
Log average gross monthly wages of tert. educ.	9.0834	9.0014	0.0000
Percentage of workers with VET degree	0.5312	0.3728	0.0000
Firm size	123.7275	80.9336	0.0000
Male	0.6183	0.5663	0.0000
Tenure	8.2857	8.0342	0.0000
Age	41.1377	40.7388	0.0000
Part-time	0.2589	0.2545	0.2272

Source: Swiss Earning Structure Survey 1998-2004; authors' calculations

We also investigate the relationship between the instrument and the dependent variable by estimating the reduced form. The results from this estimation appear in Table A4.1 in the Appendix. In the reduced form, the instrument has a positive and statistically significant effect on the average productivity of tertiary-educated workers. Thus both the mean value comparison (Table 4.2) and the results from the reduced form support the credibility of our instrument.

Table 4.5 shows the first- and second-stage results from our IV estimation. A comparison of the F-statistic with the critical values reported in Stock and Yogo (2002) show that the hypothesis of a 5% bias of the IV estimation is rejected not more than 15% of the time. Moreover, the results of the first stage show that the effect of the dummy indicating a German-speaking region on the number of workers with VET degrees is positive and highly significant (at the 1% level). Both results indicate a strong instrument. Firms in German-speaking major regions employ more workers with VET degrees than firms in non-German-speaking major regions. The instrument captures those firms that would change their training behavior according to the culture that the region indicates.

Table 4.5 Linear Spillover Effects of Workers with VET on Workers with Tertiary Education (Instrumental-Variable Estimation)

IV Estimation	First Stage	Second Stage
Dep. Var.:	Number of workers with VET degree	Log average gross monthly wages of tert. educ.
Number of workers with:		
Tertiary Education	1.09066***	-0.23004
	(6.63)	(-1.57)
VET		0.21350*
		(1.65)
Other	0.38367***	-0.08101
	(6.03)	(-1.59)
Instrument:		
German-speaking region	0.13934***	
	(3.10)	
Controls		
Firm characteristics	yes	yes
Regional controls	yes	yes
Sector controls	yes	yes
Year controls	yes	yes
F Statistic	9'612	
N	22,846	22,846

Note: Cluster-robust t-statistics in parentheses (Cluster level: Firm). Number of workers was divided by 100.
* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

As hypothesized, the second stage estimation results show a positive effect for the number of workers with VET degrees on the productivity of workers with tertiary education. This estimate is statistically significant at the 10% level. The positive sign shows, together with the results from the OLS and FE estimations, that we still can support our first hypothesis.

4.5.4 Robustness check: Industry level estimation

The benefit received by tertiary-educated workers from interacting with workers with VET degrees might differ across industries. First the industry-specific educational distribution might differ. Second, knowledge differences between tertiary-educated workers and workers with VET degrees might be industry-specific. Thus the spillover effect depends on whether tertiary-educated workers and workers with VET degrees work in related occupations and whether the workers with VET degrees have knowledge relevant for the productivity of tertiary-educated workers. As the number of occupations differs across industries, spillover effects between workers with different sets of knowledge might also differ across industries.

To analyze industry-specific differences in the relationship between the productivity of tertiary-educated workers and the number of workers with VET degrees, we divide our sample by sector into different subsamples. For each subsample, we calculate the average number of workers with tertiary education per firm and divide this number by the average firm size of the sector. Table 4.6 shows the calculated values for the education sector (highest value), the hotel and restaurant sector (lowest value), and the manufacturing sector and the health and social work sector (two sectors representing values very close to the overall mean).

Table 4.6 Distribution of the percentage of tertiary educated workers within selected sectors

Sectors	Percentage of tertiary educated
Manufacturing	20.08
Hotel and restaurants	9.56
Education	70.87
Health and social work	21.23

Source: Swiss Earning Structure Survey 1998-2004; authors' calculations

Table 4.7 shows the estimation results for equation (4.6). For all of the selected sectors, we find similar results, which are in line with our main findings: The coefficient for the number of workers with VET degrees is positive and statistically significant for all sectors. The coefficient of the corresponding squared term is negative and statistically significant for all sectors. Comparable to our main results, we observe positive but diminishing returns for tertiary-educated workers from the employment of workers with VET degrees. This result changes only for very large firms i.e. for those firms with more than 2287 VET workers. Thus, for the majority of firms, we find support for hypotheses H1 and H2.

Table 4.7 Non-Linear Spillover Effects of Workers with VET on Workers with Tertiary Education (OLS Estimation in Seclected Sectors)

OLS Regressions	Manufacturing	Hotels and restaurants	Education	Health and social work
Dep. Var.: Log average monthly wages of tert. educ.				
Number of workers with:				
Tertiary Education	-0.02028*	-0.70798*	0.01162	-0.16750***
	(-1.85)	(-1.68)	(0.19)	(-3.73)
VET	0.02882***	0.21787***	0.94855***	0.08572***
	(3.26)	(3.12)	(4.93)	(5.87)
Other	-0.00371	0.00788	-0.50825*	0.01697
	(-0.42)	(0.11)	(-1.75)	(0.91)
Sq. number of workers with:				
Tertiary Education	0.00069	0.96087	-0.00083	0.00847
	(1.64)	(0.69)	(-0.06)	(1.30)
VET	-0.00063***	-0.01474**	-0.99173***	-0.00186**
	(-2.81)	(-2.49)	(-4.62)	(-2.09)
Other	-0.00020	-0.00041	1.01163**	-0.00107
	(-0.49)	(-0.19)	(2.46)	(-1.51)
Controls:				
Firm characteristics	yes	yes	yes	yes
Regional controls	yes	yes	yes	yes
Year controls	yes	yes	yes	yes
R-squared	0.11	0.16	0.19	0.10
N	6,661	718	1,321	1,793

Note: Cluster-robust t-statistics in parentheses (Cluster level: Firm). Number of workers was divided by 100.
* Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

4.6 Discussion

This paper analyzes the impact of the educational composition of the workforce in a firm on the productivity of workers. Other than previous literature we analyze reverse spillover effects, i.e. the effects of workers with secondary education on workers with tertiary education in the same firm. We argue that such spillover effects occur because knowledge spillovers not only result from the differences in the level of education but also in the type of education. While workers with tertiary educations are assumed to possess more theoretical knowledge, workers with dual-track VET possess more practical and operational knowledge. Therefore, tertiary-educated workers gain from working together with VET-workers; they might e.g. learn from workers with VET degrees how to enhance the implementation of a new technology into an existing one.

We analyze our hypotheses using a large Swiss employer-employee data set. Our results show that an increase in the number of workers with VET degrees has a positive but diminishing effect on the productivity (measured in average wages) of workers with tertiary education. The results remain robust against the inclusion of several control variables, such as regional, sector, and year controls and do not depend on firms' location in the educational distribution. Furthermore, the results are stable if we include a firm fixed effect and take potential endogeneity of the employment of workers with VET degrees into account. All specifications are in line with our hypotheses.

Our results have several policy implications. Unlike the recommendation by Aghion and Howitt (2006) to generally increase tertiary educated in developed economies, we argue that it pays to keep a well-balanced mix with vocationally educated workers (as opposed to unqualified workers). Even with stronger emphasis on tertiary education, firms should not neglect the importance of strong investments in the training of workers with good vocational skills, particularly on the secondary level. Workers with dual-track VET are highly qualified workers with professional knowledge that contributes to the productivity of workers with a tertiary education. Increasing the number of workers with a tertiary education may be an adequate strategy if jobs require only primarily theoretical work or require workers to perform their own research. As soon as production and implementation of knowledge is involved it pays to also employ a substantial number of highly skilled VET workers. That also asks for a regime shift in human capital investments towards a stronger investment of firms in building the human capital stock instead of merely relying on the schooling/university system and state financing.

Appendix 1

Swiss Educational System

In Switzerland, compulsory education ends after 9 years of schooling. Students then have the choice of continuing their education either on an academic or vocational education path. For the academic path, which leads to a university admission certificate, an admissions test is required (Annen et al., 2010; p.126). The vocational path leads to a VET degree and combines over 2-4 years of on-the-job training with theoretical education. Apprentices usually have 3-4 days per week of on-the-job training and 1-2 days per week of theoretical education. The structure of the training and the centralized final examination (both theoretical and practical) makes dual-track VET within an occupation comparable across firms.

Completed upper secondary education is the prerequisite for beginning tertiary education. Both tertiary education and upper secondary education have an academic and a vocational path. While switching from an academic upper secondary path to a tertiary vocational path or vice versa is possible, these changes require admissions tests. The tertiary academic path entails education at either a university or at one of the two federal institutes of technology. Graduates from these institutions can continue their education at the doctoral level. Students with an upper secondary academic background enter tertiary academic education without needing to take an admissions test. The tertiary vocational path entails education at a university of applied sciences (e.g., arts, humanities), a pedagogical university, or higher vocational school and takes 3-5 years of studying. Students with an upper secondary vocational background do not have to take the admissions test. With certain restrictions, graduation from a university of applied science or a pedagogical university entitles the graduate to begin a doctoral program at a university or a federal institute of technology depending on the quality of the completed education.

Appendix 2

Table A4.1 Linear Spillover Effects of Workers with VET on Workers with Tertiary Education (Reduced-Form Estimation)

OLS Estimation	Spec. (1)
Dep. Var.: Log average gross monthly wages of tert. educ.	
Number of workers with:	
Tertiary Education	0.00281
	(0.98)
Other	0.00090
	(0.54)
Instrument:	
German-speaking region	0.02975*
	(1.86)
Controls	
Firm characteristics	yes
Regional controls	yes
Sector controls	yes
Year controls	yes
R-squared	0.19
N	22,846

Note: Cluster-robust t-statistics in parentheses (Cluster-level: Firm). Number of workers was divided by 100. * Statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Chapter 5 Conclusion

This dissertation analyses the influence of dual-track vocational education and training (VET) on innovation and productivity at the firm level. Knowledge from vocational education has largely remained unconsidered to have positive effects on these two outcomes. Rather recent models predict a negative association between vocational education and innovation and productivity in highly dynamic environments (Aghion & Howitt, 2006; Krueger & Kumar, 2004a, 2004b). These models cannot explain the case of Switzerland, a highly innovative country that strongly relies on workers with secondary vocational education. As Swiss secondary vocational education has a high quality (Bierhoff & Prais, 1997) and high training standards (Ryan et al., 2010), the aim of this dissertation is to analyze the benefits firms gain from secondary vocational education.

Chapter two analyzes the influence of VET on firms' innovativeness. After building a theoretical model that identifies similarities of dual-track VET to academic education, this chapter shows that curricula in dual-track VET improve knowledge diffusion within the Swiss VET system. Research on the role of knowledge in VET system has mainly focused on the integration of new knowledge rather than on an analysis of diffusion mechanisms (Backes-Gellner, 1996; Gonon & Maurer, 2012). The analyses of the integration of new knowledge shows that future-oriented knowledge is frequently included in the Swiss VET system (Busemeyer & Trampusch, 2012; Wolter & Ryan, 2011). Although the inclusion of new knowledge is an important factor for innovation, properly defined diffusion mechanisms enhance the innovativeness of firms participating in VET (Lucas, 2009; Staley, 2011). Thus the identification of diffusion mechanisms within the VET system is of central interest for innovation policy.

The model derived in this chapter can show that due to the application of training curricula and the combination of workplace training and vocational schooling, new knowledge enters those firms that participate in dual-track VET. Thus this chapter integrates the training curricula as an additional asset in the knowledge production function of training firms and hypothesize that firms that participate in dual-track VET are more innovative than firms that do not participate. For the estimation of the knowledge production function Swiss survey data provided by the Swiss Economic Institute (KOF) are used. Innovation is operationalized using four measures (general innovation, product innovation, process innovation and patent applications). The empirical approach considers potential endogenous training decision and uses a set of two instruments (firm age and firm language) to overcome endogeneity problems. The estimation results show a positive and highly significant association between training and all innovation outcomes. If endogeneity of training is considered, the estimation results show statistically significant effect of training participation on general innovation. This effect is positive and remains stable throughout several specifications. Moreover the results show that if training intensity is controlled, training participation still is positively associated with innovation. The results are consistent with the model derived in the theory section of this chapter. Training participation has a positive effect on firms' innovativeness.

The findings of this chapter show that dual-track VET has a positive effect on firms' innovativeness. These findings are contrary to standard theory that treats secondary vocational education as an innovation hampering factor for highly innovative environments. Our theoretical model shows that the mechanisms within vocational education play a crucial role for its innovation potential. It is not only the integration of new knowledge into the VET system that is important, but also its diffusion plays a central role for innovativeness of training firms. Our analysis of knowledge diffusion mechanisms concentrates on the curriculum but is not limited to it. Other diffusion mechanisms that might work through VET teachers (Backes-Gellner, 1996) and training in inter-company courses can enhance the speed of knowledge diffusion with the VET system. The identification of these mechanisms and their empirical analysis constitutes a promising field for future research.

The findings of the second chapter have several theoretical and practical implications. Updating training curricula appears to be the key factor for the positive influence of dual-track VET. Although employee associations have an own interest to keep curricula updated, fostering communication among social partners and stakeholders might improve the identification of new technological trends in an occupation. This constant updating of curricula might also influence training behavior of non-training firms. If the benefits of the knowledge diffusion appear to be large enough, backward non-training firms might consider training as a possibility to catch-up with the technological development in an industry. The positive influence of dual-track VET should also be considered in cost-benefit calculations of training (e.g., Wolter et al., 2006). As long term benefits of innovation are difficult to estimate, firms' monetary benefits of dual-track VET might underestimate their real benefits. The potential for long term benefits that firms might realize, underline the importance of a long-term perspective in training decisions.

By showing that firms benefit from participation in VET, we established VET as an external knowledge source for training firms. But also internal knowledge sources like the firms' workforce have implications for firms' innovativeness. The knowledge of a firms' workforce stems from different educational levels and types. Workers with VET degrees are an essential part of many firms' workforces. Thus, not only the inclusion of knowledge from dual-track VET due to training is of interest but also the potential for workers with VET qualification to share their knowledge with other workers.

The third chapter of this dissertation therefore analyses how firms combine human capital and HRM practices to achieve superior innovation performance. Based on HR models, this chapter develops the integration of human capital and HRM practices in the innovation context. The theoretical HR literature considers complementarities between different levels and types of human capital and between single HRM practices in a configurational approach for more than five decades (Burns & Stalker, 1961; Delery & Doty, 1996; Miles & Snow, 1984). Although several HR theories and typologies integrate human capital and HRM practices in a configurational way, only little is known on the mechanisms within these typologies and their implications for innovations of firms. As recombinations of knowledge generate new knowledge and thus innovation (Kogut & Zander, 1992), this chapter develops a knowledge creation (KC) system that considers knowledge stocks (human capital pool) and knowledge flows (induced by a firm's HRM system) (Wright et al., 2001). The analysis of complementarities within and between the human capital pool and the HRM system explicitly focuses on innovation. The results of this analysis show that innovation-relevant complementarities exist within and between the human capital pool and the HRM system. This theoretical development provides an augmentation of classical HR theory by linking the configurational approach directly to innovation.

Empirical studies that integrate human capital and HRM practices to analyze firms' innovation performance apply a contingency approach (De Winne & Sels, 2010). The empirical analysis in chapter three deviates from this approach and analyzes the KC system from a configurational perspective to capture complex complementarities with the system. Thereby a methodology that is consistent with theoretical requirements of the configurational approach e.g., equifinality and causal complexity is applied. This method, the fuzzy set qualitative comparative analysis (fsQCA), allows the identification of multiple configurations of the KC system that are equally effective in explaining superior innovation performance.

The empirical analyses bases on data of manufacturing firms from the Innovation Survey of the Swiss Economic Institute (KOF). The analysis includes information on the qualification of the workforce in educational degrees, HRM practices, environmental dynamism and firm size. The identified configurations differ largely by the underlying environmental dynamism and the design of the human capital pool and HRM system. Based on the configurations the third chapter derives a taxonomy with four types that aggregate the underlying patterns of the identified configurations. Two types are consistent with earlier types described by Burns and Stalker (1961). The concentration on a single skill combined with rather no use of HRM practices resembles a type that is successful in lowly dynamic environments. This configuration is consistent with the mechanistic form of the Burns and Stalker (1961) typology. On the other extreme we find a type that combines concentration on skills from tertiary education (academic and vocational) and a HRM system that combines teamwork with empowerment. This type is labeled “empowerment” and is connected with a high environmental dynamism. This type is consistent with the organic form of the Burns and Stalker (1961) typology. The remaining two types are hybrid and are both connected to a highly dynamic environment. The “vocational skill mix” type combines a concentration on vocational skills at both, the secondary and the tertiary level. The HRM part of this type is rather limited and focuses on the application of teamwork. This type generates its superior innovation performance from the use of a common language that eases the knowledge flow among workers. The “organizational learning” type concentrates on single skills but applies a large set of HRM practices (teamwork and job rotation) that diffuse knowledge and lead to organizational learning.

The findings of chapter three have implications for a further refinement of the Burns and Stalker (1961) typology. The hybrid cases can be integrated in this typology from a static or dynamic perspective. The static perspective would regard the hybrid types as fixed systems that explain superior innovation performance. From a dynamic perspective the hybrid types might picture transitory stages of firms that aim at adopting one of the extreme forms (mechanistic or organic). Both perspectives provide starting points for empirical and theoretical research on KC systems. Further empirical research on temporal dynamics within a KC system could show whether the types identified in chapter three constitute transitory stages or are rather fixed.

The findings of the third chapter also have important implications for practitioners. First they show that different configurations of a KC system can explain superior innovation performance. A best practice solution that provides general advice for building a KC system does not seem to exist. Nevertheless the types support practitioners in establishing and refining the KC system of their firm. The types outline mechanisms that explain superior innovation performance. For example the configurations show that concentrating on hiring journeyman and master craftsmen is a part of a strategy that explains superior innovation performance. These workers use a common language and common terminologies and thereby facilitate the knowledge flow within the firm. Sticking to this example, the presence of a common language might reduce the necessity for formal practices that induce knowledge exchange like job rotation. Thus the types could serve as recipes that allow firms to compare the configuration of their KC system with a configuration that is known to generate superior performance.

One part of the KC system that is analyzed in chapter three is the human capital pool. Within this human capital pool complementarities between different educational levels and types occur. Due to interactions among workers, knowledge is shared and new knowledge can be generated. The sharing of knowledge is directly linked with innovation but might also have implications for workers' productivity. Due to learning from co-workers, a worker receives information on how to perform tasks. This knowledge increases his or her productivity. These educational spillovers have been extensively analyzed in the literature (e.g., Ciccone & Peri, 2006; Moretti, 2004b; Wirz, 2008). The subjects for analysis in this literature are either spillover effects from the highest educational level (e.g., Moretti, 2004b) or the average educational level (e.g., Rauch, 1993). As educational spillovers result from differences in knowledge, the distinction of education by level appears to explain only a part of knowledge differences. In countries that have highly developed vocational and academic educational paths like Switzerland a considerable amount of knowledge differences between workers can be explained by educational type.

Chapter 4 analyzes educational spillover effects from secondary vocational education to tertiary education, thereby looking at the reverse direction of traditional spillovers. The theoretical model of this chapter reduces educational spillovers to informational spillovers. According to Jovanovic and Rob (1989), informational spillovers depend on knowledge differences among workers. This simplification of educational spillovers allows the inclusion of educational type as an additional dimension that explains knowledge differences. According to this reasoning chapter four expects that workers with tertiary education benefit from interacting with workers with completed dual-track VET. This benefit might not be linear. Workers that interact with their co-workers benefit more from an initial interaction than from following interactions as the majority of knowledge might be transferred during initial interactions. Similarly, if the probability of interactions with a certain group of co-workers that have similar knowledge increases due to hiring, workers might benefit more from an increase of a small group than from an increase of a group that is already large. Thus this chapter expects that workers with tertiary education have positive but declining returns from interacting with their colleagues with VET-degrees.

The empirical analysis of this chapter bases upon data from the Swiss Earning Structure Survey. The estimation strategy follows Martins and Jin (2010) and aggregates a Mincerian earnings equation to the firm level. To measure the productivity of workers with tertiary education, aggregated wages are used. As the number of workers with completed dual-track VET might be endogenous, an instrument that explains firms hiring preferences is used. Different approaches, pooled OLS, FE estimation and IV estimation, show a highly significant effect of workers with completed dual-track VET on productivity of workers with tertiary education. This effect is positive and declining and thus meets the expectation of the theoretical development of this chapter.

The findings show that spillover effects also take a different direction if type instead of level is considered. Furthermore, they show a curvilinear functional form of the spillover effect. Dual-track VET has besides its own contribution to productivity also effects on co-workers. These effects should be considered in further studies that analyze costs and benefits of dual-track VET. Moreover the findings underline that the productivity of a single worker depends on the education and skills of their co-workers. Firms therefore influence workers performance by integrating him or her in a productive environment. To give a practical example: Engineers might not develop their full productivity if they collaborate with unskilled production workers. Instead combining engineers with highly skilled production workers, who can give engineers valuable feedback, might leverage engineers' productivity.

In sum, this dissertation shows that Swiss dual-track VET provides a valuable source for a firm's innovativeness and productivity. Despite its just mentioned implications for firms, educational systems and policy makers, this dissertation has also implications for economic research. In general, growth models consider vocational education as inappropriate to produce innovations at the technological frontier. Future research that investigates the relationship between education and growth could consider the quality of education and the functions of educational institutions (e.g., curricula might facilitate knowledge diffusion). Quality of education and knowledge diffusion potential of an educational system could complement traditional measures like educational level and help refining growth models.

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